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Joint fleet size and charging station location planning for integrated demand responsive transport service using electric vehicles

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Contents

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Abstract

Electric vehicles have gained popularity over past decades as they are more environmentally friendly than conventional gasoline vehicles. This thesis studies the optimization of joint fleet size and number and location of charging stations location problem for integrated demand responsive transport (DRT) service using electric vehicles. We propose a simulation-optimization framework to model the problem and solve it approximately using a two-stage approach. Under the given framework we firstly determine the minimum fleet size which satisfies a predefined level of service (LOS) criterion, and then optimize the charging infrastructure using a surrogate-based approach. The proposed method is tested using both a generated dataset and a Luxembourg dataset. The result shows that installing 18 new DC Fast chargers in optimal locations in Luxembourg can decrease the average charging operation time of EVs (electric vehicles) by 45.1%. A comparison with another charging station allocation method k-means also proves the efficiency of the proposed method.

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Symbols and abbreviations

T	Set of types of chargers
c^v	Price of an electric vehicle
n	Fleet size
c_j	Unitary cost of chargers of type j
k_j	Number of chargers of type j
x_v	Distance travelled by vehicle v for a full-day operation
c^{opr}	Cost of electricity consumption and maintenance per kilometer travelled
t_v^w	Total charging access time during one day operation for vehicle v
γ	Conversion coefficient of out-of-service time to cost
ϕ	conversion coefficient of investment to annual cost
k_{ij}	Number of type j chargers at charging station i
$\hat{k}_i$	Maximum number of chargers at charging station i
S	Set of charging stations
B_v	Initial battery state of charge of vehicle v
$\hat{B}$	Electric vehicle battery capacity
e_{ij}	Energy consumption travelling from location i to j
θ	Low battery threshold (percentage)
$B_{vi}(t)$	Battery state of charge of vehicle v at location i at time t
$w_{vij}(t+\pi_{ij})$	Waiting time of vehicle v currently located at location i, arriving at charging station j at time $t+\pi_{ij}$
$T_{vij}(t+\pi_{ij})$	Time spent on charging when arriving at charging station j at time $t+\pi_{ij}$ for vehicle v
η_j	Power output of type j charger

DRT	Demand responsive transport
LOS	Level of service
MoD	Mobility on demand
EV	Electric vehicle
SoC	State of charge
RBF	Radial basis function
PT	Public transport

Chapter 1

Introduction

1.1 Background

Public transport has always played an important role in the society. It provides people with mobility and access to schools, hospitals, and other destinations with a certain frequency. It also relieves road congestion and helps to reduce pollution. Basically, traditional public transport only provides a fixed route mobility service. In many rural areas, the frequency of public transport is low (longer customer waiting time), it may appear less desirable compared to a demand responsive transport (DRT) system which is flexible and user-centered. Nowadays, DRT system has risen in importance, as it's more flexible and user-centered than public transportation and provides an alternative to car use. It also overcomes the first/last mile problem of fixed-route transportation where passengers need to travel from the origin to the public transit station or from the transit station to the destination. Moreover, in rural and suburban areas, the public transport infrastructure is usually not well-developed because of the limitations of population density, and the DRT system can function as a complement of public transport. Some commonly seen examples of demand responsive transportation are taxi, Uber and flexible shuttle service.

The planning of demand responsive transport system needs to consider the trade-off of operation cost and user inconvenience (Fu & Teply (1999)). From the perspective of service providers, the goal is to minimize the cost of the operation, which can be achieved by reducing the number of vehicles and increasing the number of user-service route matches, etc. (Stiglic et al. (2018)); while from the perspective of the riders, the objective is to minimize the inconvenience, which can be realized by minimizing travel distance, travel time or travel expenses (Agatz et al. (2012)). To optimize this system, a number of configuration parameters such as fleet size, capacity and routing need to be optimized. These are referred to as supply-side decision variables. However, due to the stochastic and dynamic nature of user-demand, the optimization problem can not be solved using exact mathematical methods. Furthermore, each experiment for one simulation run can be time-consuming. Optimization methodologies such as the surrogate optimization provide an efficient way to optimize the configuration of the system with few expensive function evaluations.

Electric vehicles have gained popularity over past decades as they are more environmentally friendly than conventional gasoline vehicles. The major benefit of electric vehicles is that they produce no carbon dioxide, can use renewable energy, and is more energy-efficient. Many transport network companies like Uber and Via (https://ridewithvia.com/) start their fleet electrification towards sustainable mobility solutions (George & Zafar (2018)). In this thesis, we consider the planning of integrated DRT using a fleet of electric vehicles/shuttles. The service planning involves tactic decisions regarding number and locations of charging stations, and number of vehicles (fleet size). The next part of this chapter is a literature review, which is organized as follows. Firstly, we will describe DRT and integrated DRT system. Secondly, the supply-side decision variable optimization methods are discussed. Finally, an outlook of this thesis is presented.

1.2 Literature review

1.2.1 DRT, integrated DRT and EV charging management

(1) DRT system

According to Kirby et al. (1974), a demand responsive transport "provides door-to-door service on demand to a number of travelers with different origins and destinations". Figure 1.1 shows how a DRT system works. As can be seen, passengers need to call in requests in advance, informing the service provider of their origin/pick-up points. Apart from the fixed route, the vehicle will also travel the deviation route to pick up the other passengers.

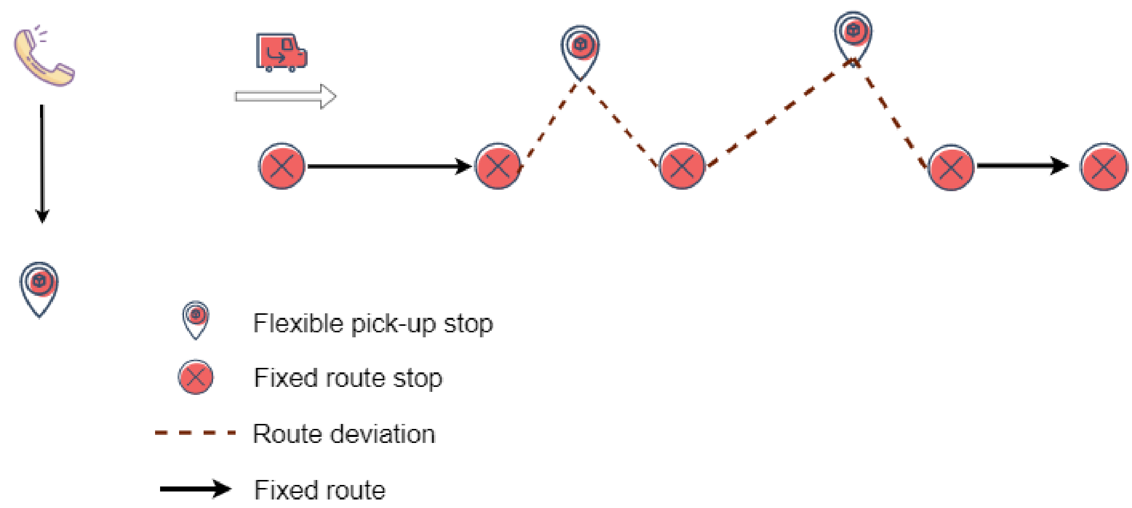


Figure 1.1: Example of demand responsive transport system (adapted based on Häll (2006))

For planning a DRT system, one of the questions is when DRT service is better than fixed route service. Li & Quadrifoglio (2010) pointed out that the turning point should be in the range from 10 to 50 customers/$mile^2$/h, and the DRT service is preferred during peak hours. As a DRT service is usually provided within some specific areas, studies have been conducted to find the optimal zones for DRT service. Lee & Savelsbergh (2017) found that in areas where transit points are closer to each other, a DRT service is preferred over fixed route service. Another important issue in designing a DRT system is to determine supply-side parameters. In the work of Winter et al. (2016), the influence of fleet size on the performance of the system is analyzed, and designing of an automated DRT system is presented.

(2) Integrated DRT System

According to Häll (2006), an integrated demand responsive transport system is a combination of a demand responsive service and a fixed route service (public transport). It's a system where passengers will travel the first/last mile by DRT, which works as a complement of the public transit. Figure 1.2 presents how an integrated DRT system operates. The DRT vehicle picks up passengers from their origins along the route, and takes them to the transfer point which connects the fixed route and DRT. Passengers will then travel by public transport, and switch to DRT at the transfer point to get to the destination.

The integrated DRT planning problem aims to find the optimal supply-side parameters such as fleet size and routing to maximize profit. Liu et al. (2009) used genetic algorithm to determine the fleet composition and routing. Repoussis & Tarantilis (2010) combined a novel knowledge extraction mechanism with a probabilistic semi-parallel construction heuristic to obtain the solution. Liu et al. (2019) applied a Bayesian optimization method to find the optimal parameters, where the integrated DRT system is regarded as a blackbox function and Bayesian optimization is used as a sequential search strategy. Some recent studies show integrated DRT service could increase ridership of public transport and provide customer's seamless door-to-door mobility service (Ma (2017), Ma et al. (2018), Ma et al. (2019), Häll et al. (2009)).

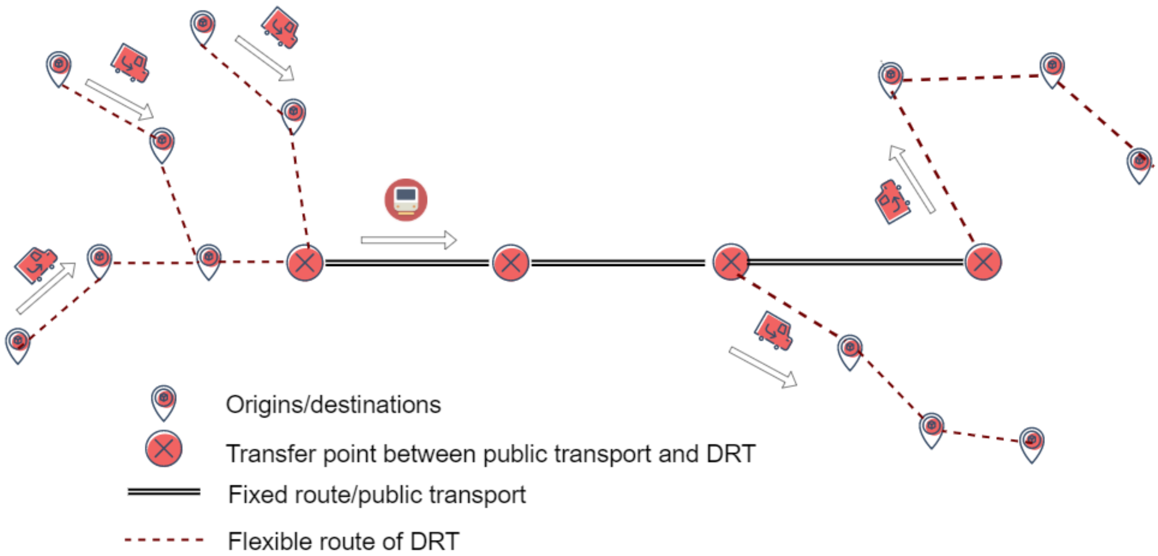


Figure 1.2: Integrated DRT system (adapted based on Häll (2006))

(3) Electric vehicle charging management

Electric vehicles have numerous benefits compared to conventional vehicles such as environmentally friendly and energy efficiency. With the rapid rise in the use of electric vehicles, it also raises a problem as to how to manage the charging of electric vehicles. Most studies focus on private EV charging demand management (Shen et al. (2019)).

Commercial electric vehicle charging management received more attention in recent years. According to Amjad et al. (2018), there are three types of EV charging management approaches: centralized EV charging which provides centralized control, distributed EV charging which allows EV to make decisions, and the third EV charging approach is a combination of the two. Researchers have also proposed methods to achieve various objectives. For instance, Mkahl et al. (2017) adopted a linear programming method to make sure the battery SoC (state of charge) level is at its highest when reaching the charging station. In He et al. (2012), an optimal scheduling scheme is proposed to minimize the total cost of EVs performing charging and discharging during the day.

1.2.2 Supply-side decision variable optimization

The optimization problem is the problem of choosing a set of values for supply-side variables of an integrated DRT system, such as vehicle capacity, fleet size, etc. To optimize an integrated DRT system, the supply-side variables need to be tuned so that the optimal configuration can be obtained. When simulating an integrated DRT system, the supply-side variables are used to configurate the system and they are not updated during the simulation process. The supply-side variable optimization problem is similar to the hyperparameter optimization problem in machine learning. Hence many hyperparameter optimization techniques can be applied to our problem. This section will present different methods of supply-side decision variable optimization.

(1) Grid search

Grid search is a frequently used method for determining the supply-side decision variables of DRT systems. The optimal values of the variables will be selected from a set of trial values. In a grid search method the candidate points are predefined, the one that gives the optimal objective function value will be chosen (Liu et al. (2009)). However, in case of high dimensions, the performance of this method is compromised because of the curse of dimensionality. Therefore, a more commonly used method is to combine manual search and grid search. For instance, Larochelle et al. (2007) manually selected around 100 configurations of hyperparameters for a neural network algorithm, and then grid search is used to search within the predefined configurations to find the optimal one.

(2) random search

Random search is an algorithm where samples (i.e. candidate points) are randomly drawn from the parameter space. Each configuration of parameter is evaluated by the loss function, thus the optimal one can be selected (Bergstra & Bengio (2012)).

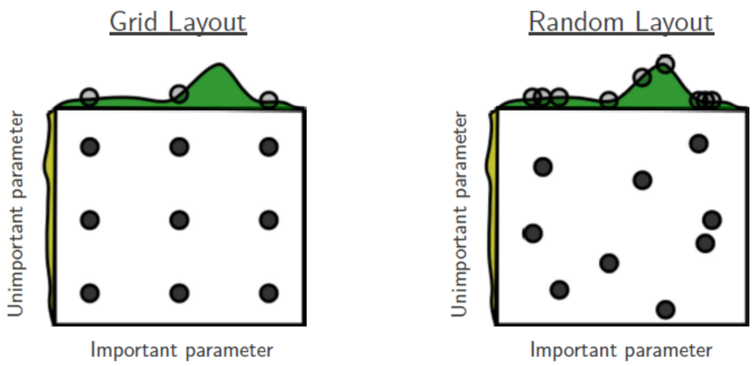


Figure 1.3: Grid search and random search (Bergstra & Bengio (2012))

Figure 1.3 shows the logic behind grid search and random search. According to Bergstra & Bengio (2012), random search performs better than grid search when some parameters are more important than others. Furthermore, when correlation exists among parameters, random search is able to find the optimal solution in less trials than grid search. However, it should be noted that for both grid search and random search, it is not guaranteed that a local minimum can be obtained since only samples from the search space are evaluated.

(3) Surrogate optimization

When the loss function is overly expensive to evaluate, a surrogate model can be used to approximate the real loss function and help identify potential optimal configuration. The surrogate model based optimization is useful for speeding up the optimization processes. According to Queipo et al. (2005), the basic framework of surrogate-based optimization can be illustrated as follows:

1. Construct surrogate model from initial observations to approximate true objective function.
2. Estimate objective function value at candidate points using the surrogate function.
3. Evaluate true objective function value at the estimated minimum.
4. Update surrogate with the new observations until convergence.

In recent years various surrogate modelling approaches have been proposed, such as kriging models (Martin & Simpson (2005)), radial basis functions (RBF) models (Regis & Shoemaker (2007)) and support vector machine models (Collobert & Bengio (2000)). In the work of Ma & Xie (2020), the surrogate optimization model is used to solve an optimal fast charging station location problem.

(4) Bayesian optimization

The main idea of Bayesian optimization method is to select candidate points for objective function evaluation using posterior distribution. For instance, Liu et al. (2019) combined prior (obtained through online pilot survey) and likelihood of data (obtained from simulation) to get a posterior. The posterior selects the next set of decision variables to be evaluated in the simulation, and then update the posterior with newly acquired data.

The work of Eggensperger et al. (2014) shows how Bayesian optimization method can be combined with spearmint, sequential model-based algorithm configuration and tree Parzen estimator.

The advantage of Bayesian optimization method is that it can work directly with black-boxes (Solnik et al. (2017)). The disadvantages are also clear, which are: (1) when it comes to high dimensional problems, the efficiency of Bayesian optimization is similar to that of random search (Li et al. (2016)); (2) Since Bayesian optimization method is a Gaussian process which assumes continuous input, it can not work on categorical data (Garrido-Merchán & Hernández-Lobato (2019)).

(5) Gradient-based optimization

Gradient-based optimization uses search directions defined by the gradient of the function at the current point to solve optimization problem (Wikipedia (2019)). In hyperparameter optimization, exact gradients of cross-validation performance can be computed for all hyperparameters using chaining derivatives (Maclaurin et al. (2015)). In the work of Maclaurin et al. (2015), this method has been developed to handle up to thousands of hyperparameters.

For the integrated DRT system planning, **Figure 1.4 shows the framework of sypplyside decision variable optimization for planning an integrated DRT system.** The framework consists of two parts: the simulation process and the optimization process. In simulation process the user demand and public transport will be generated. Given the supply-side configuration parameters, the DRT service can be optimized/generated. Therefore, an objective function value can be obtained as an output to evaluate the performance of the system. Based on this value, the supply-side variable values will be updated, which will lead to updated system configuration. The new configuration will be used as input for the next iteration of simulation. The iteration process stops when a stopping criteria is satisfied.

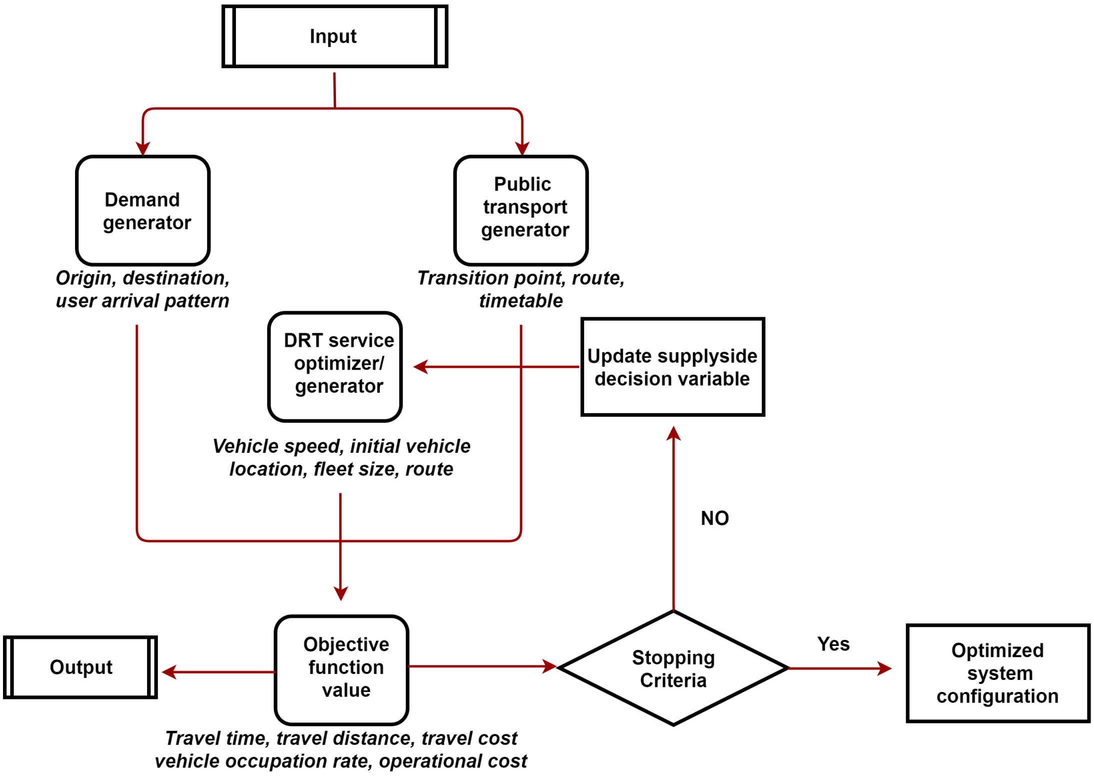


Figure 1.4: Framework of Supply-side variable optimization for integrated DRT system (adapted based on Liu et al. (2019) and Winter et al. (2016))

1.2.3 Outlook

The plan of this master thesis work is to propose a planning scheme to integrate public transport and demand responsive transport to provide door-to-door transit service using electric vehicles. The study area will be Luxembourg, the demand data will be randomly generated, such as origin and destination of the passengers, arrival time, etc. For transit network, we will consider the OpenStreetMap and transit system in Luxembourg. The planning of this thesis work is presented in Figure 1.5. The second chapter presents the supply-side decision variable optimization model of integrated DRT system and the solution framework. In the third chapter a numerical study on a hypothetical dataset is conducted. In chapter 4 we apply the proposed model to the Luxembourg dataset, and present the results and evaluation of the method. In the last chapter we discuss the main insights and draw the conclusion.

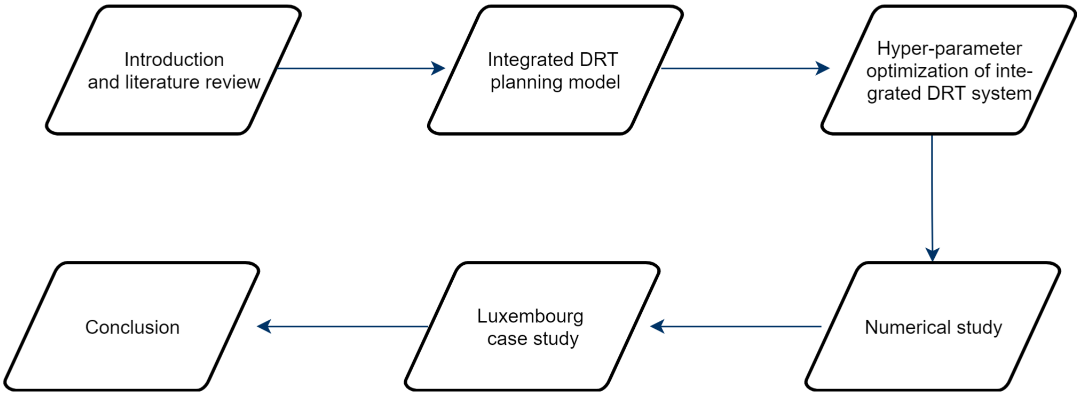


Figure 1.5: Framework of supply-side variable optimization for integrated DRT system using electric vehicles (adapted based on Liu et al. (2019) and Winter et al. (2016))

Chapter 2

Integrated DRT system planning using electric vehicles

2.1 Integrated EV-DRT planning

2.1.1 Modeling framework for the integrated EV-DRT planning

This section presents the optimization-simulation framework for the integrated EV-DRT planning. The system is composed of four components:

- **Customer demand:** Customer demand is related to stochastic ride requests, characterized by customer's pick-up location, drop-off location, and desired pick-up time.
- **Vehicle fleet:** An operator provides door-to-door transportation service or feeder service as a part of integrated rideshare-transit service with a fleet of electric vehicles.
- **Transit system:** Frequency-/timetable- based fixed-route mass transport service.
- **Charging infrastructure:** Charging infrastructure is related to charging equipment (i.e. different types of chargers) with charging stations.

The integrated EV-DRT planning problem involves in general the following three levels of decisions:

- **Strategic level:** Determine the location and capacity (i.e. number and type of chargers) of charging stations.
- **Tactical level:** Determine the fleet size of vehicles.
- **Operational level:** Determine the dispatching, routing policy and re-charging policies of EVs given charging infrastructure constraints.

We consider two criteria in the planning problem: the operator's perspective and user's perspective. The planning problem is formulated as an optimization problem to minimize operator's total cost, given the user's inconvenience constraint. The latter considers a predefined average customer waiting time. As shown in Figure 2.1, we adopt an optimization-simulation framework where we jointly consider these supply-side variables to minimize the objective function. Due to the huge design space to be explored and each simulation being computationally expensive, we will use the surrogate modeling approach to obtain approximate solutions efficiently. Note that one can formulate the problem as a bi-objective optimization problem to obtain optimal system configuration. To limit the scope, we consider the optimal configuration of charging infrastructure and fleet composition problem given a predefined vehicle dispatching, routing and re-charging policy.

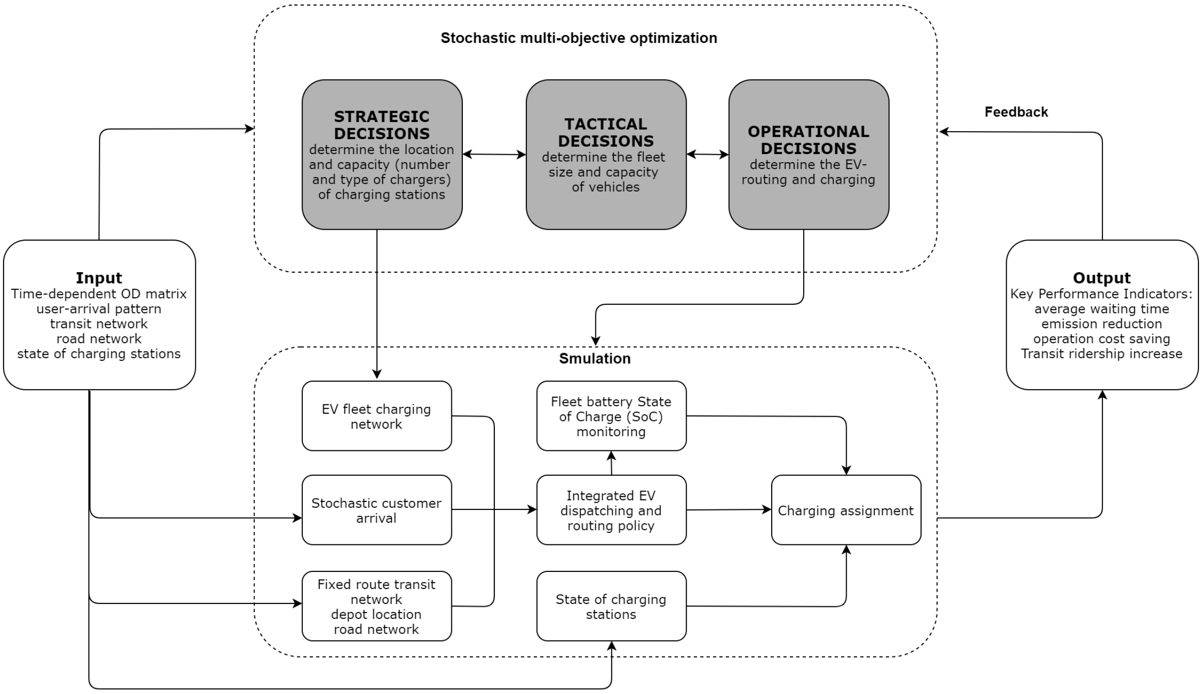


Figure 2.1: Modeling framework of the integrated EV-DRT planning

2.1.2 Problem formulation

We formulate the integrated EV-DRT planning problem as an optimization problem to minimize operator's expected annual investment and operation costs. The goal is to minimize total cost, including two terms: 1) Investment cost of fleet and charging infrastructure, and 2) operation cost. The total cost is converted to annul expected cost to be minimized (Zhang et al. (2019)). **The decision variables are the fleet size (satisfying average customer waiting time constraint) and new charging infrastructure configuration in terms of number of chargers and their spatial locations.**

(1) Investment cost

The investment cost includes EV purchase cost and charging stations investment cost. Let T be the set of types of chargers, the total investment cost can be formulated as:

$$c^v n + \sum_{j \in T} c_j k_j \tag{2.1}$$

where c^v is the price of an EV, and n is the fleet size. c_j is unitary cost of chargers of type j, and k_j is the number of chargers of type j.

(2) Operation cost

The expected operation cost is calculated on an annual basis, given assumed stable day-to-day ride request demand patterns. We assume total electricity consumption cost and maintenance cost are proportional to the travel distance of EVs. The annual expected operation and maintenance cost are defined as follows.

$$365 \sum_{v} (x_v c^{opr} + \gamma t_v^w) \tag{2.2}$$

where x_v is the distance travelled by vehicle v for a full-day operation. c^{opr} is cost of electricity consumption and maintenance per kilometer travelled. t_v^w is the total charging operation time (including travelling time to a charging station, waiting and charging time at a charging station) during one day operation for vehicle v. γ is a coefficient which converts waiting time at charging station into monetary opportunity cost when vehicles are out-of- service.

By summarizing Eq. 2.1 and Eq. 2.2, the total annual cost can be written as Eq. 2.3:

$$Z(n,k) = \phi[c^v n + \sum_{j \in T} c_j k_j] + 365 \sum_{v} (x_v c^{opr} + \gamma t_v^w) \tag{2.3}$$

where ϕ is a coefficient that converts the investment cost to an equally distributed annual cost over entire lifespan of the investment.

The integrated EV-DRT planning problem is formulated as follows:

$$Minimize \quad Z(n,k) \tag{2.4}$$

subject to

$$0 \leq \sum_{j \in T} k_{ij} \leq \hat{k}_i \quad \forall i \in S \tag{2.5}$$

$$Limited\, EV\ capacity\, and\, driving\, range\, constraints \tag{2.6}$$

$$Average\, customer\, waiting\, time\, cannot\, exceed\, a\, predefined\, threshold \tag{2.7}$$

Eq. 2.5 states that the maximum number of chargers to be installed at a candidate charging station $i \in S$ cannot exceed a predefined number $\hat{k}_i$ (Jung et al. (2014)). T is the set of types of chargers and S is the set of charging stations. Eq. 2.6 represents EV operation and re-charging constraints (i.e. charger availability at charging stations). **Eq. 2.6 and 2.7 are evaluated by simulating the dynamic ridesharing system using electric vehicles** which is an extension of the vehicle dispatching and routing model of Ma et al. (2019). The implementation detail will be presented in section 2.2.

2.1.3 Vehicle dispatching and routing policy with transit transfers

We assume an operator deploys a fleet of homogenous capacitated EVs. Vehicle dispatching and routing policy is based on the non-myopic dynamic vehicle dispatching and routing policy for ridesharing with transit transfers using conventional vehicles (Ma et al. (2019)). For each new request, three possible travel options are considered: (i) rideshare, (ii) rideshare-PT-rideshare and (iii) rideshare-PT-walk (or walk-PT-ridesahre) (see Figure 2.2). The option with least door-to-door travel time is selected to serve customers. Note that when rideshare is involved as feeder service to public transportation, customer's corresponding pickup or drop-off locations are updated. This policy assigns a new request r to a vehicle which has the lowest additional insertion cost. The reader is referred to Ma et al. (2018) and Ma et al. (2019).

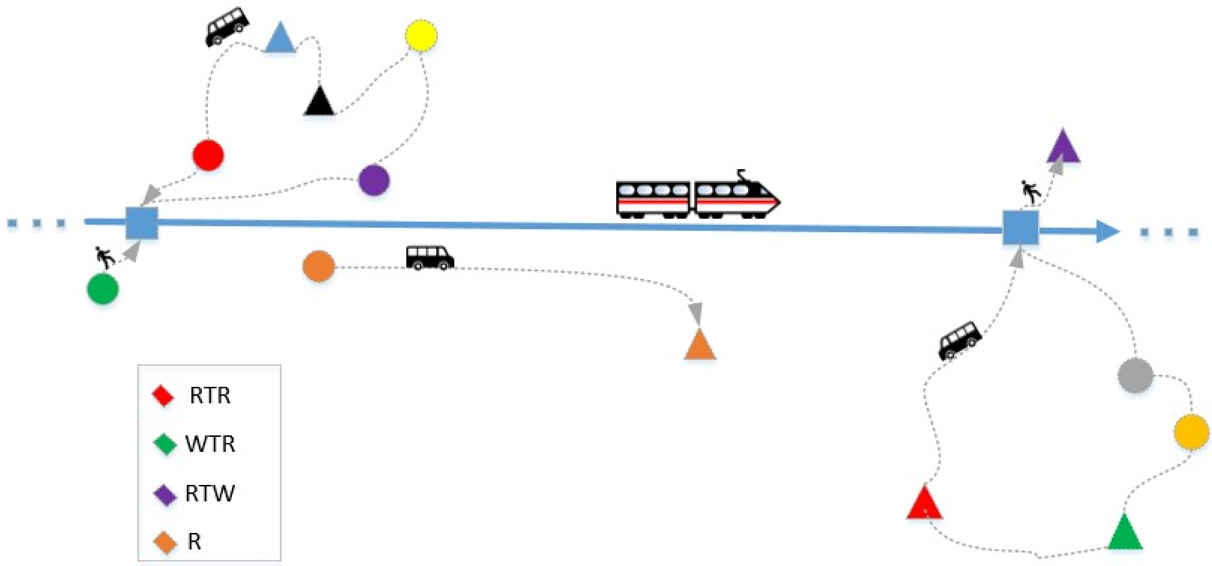


Figure 2.2: Real-time dispatching of vehicles considering two options: a) door-to-door, b) bi-modal (rideshare+transit) service with transfers (Ma et al. (2019)).

2.1.4 EV charging scheme

We assume each EV is fully charged at depots at the beginning of each day, i.e. initial battery State of charge (SoC) $B_v = \hat{B}$. The battery SoC of each EV is monitored in real-time by a dispatching center using remote communication technology. For simplification, we assume a linear energy consumption of EVs, which is proportional to travel distance (Goeke (2019)). Moreover, when the battery SoC of an EV is lower than a predefined percentage θ (e.g., 25%), a charging request is sent to the dispatching center for charging operation. The dispatching center has real-time information on the charging station status (i.e. number of available chargers, charger types, charging schedule of each charger). **We assume the operator can charge the EV fleet on its own charging stations and on the public chargers with the first-come-first-served policy.** Depending on the number of available chargers, there might be additional waiting time when arriving at an assigned charging station.

Let e_{ij} represent the energy consumption for a vehicle to travel from its current location i to j. $B_{vi}(t)$ is the remaining battery level of charge of vehicle v at node i at time t. The energy consumption from i to j is constrained by the remaining level of charge of vehicle v at time t:

$$e_{ij} \leq B_{vi}(t) \tag{2.8}$$

Given the remaining energy of a vehicle, a list of reachable charging stations is determined beforehand. **The charging station assignment of an EV is determined by the least total operation time to get fully charged policy.** This total operation time from the current position of vehicles to a charging station includes the access travel time, waiting time at charging stations and charging time to 80% full charge. The access travel time to a charging station is calculated as a shortest path travel time. Congestion effect is captured by vehicle speed considering urban driving environment. Waiting time $w_{vij}(t + \pi_{ij})$ for vehicle v currently located at i, and arriving at a charging station j at time $t + \pi_{ij}$ can be obtained based on earliest available time of any charger at station j. π_{ij} is the shortest travel time from i to j. Lastly, charging time, which depends on charger type and remaining SoC of vehicle v, is approximated as:

$$T_{vij}(t + \pi_{ij}) = \frac{(1 - \theta)\hat{B} - B_i(t + \pi_{ij})}{\eta_j} \tag{2.9}$$

where η_j is charger power output (kW). $T_{ij}(t+\pi_{ij})$ represents total time spent on charging when arriving at charging station j at time $t+\pi_{ij}$. According to Goeke (2019), the charging speed is linear until it reaches 80%, then the charging speed decreases. We assume EVs charge to 80% (i.e. θ=0.2) to allow higher vehicle availability to serve customers compared to 100% full-charge policy. The charging scheme is shown in Fig. 2.3.

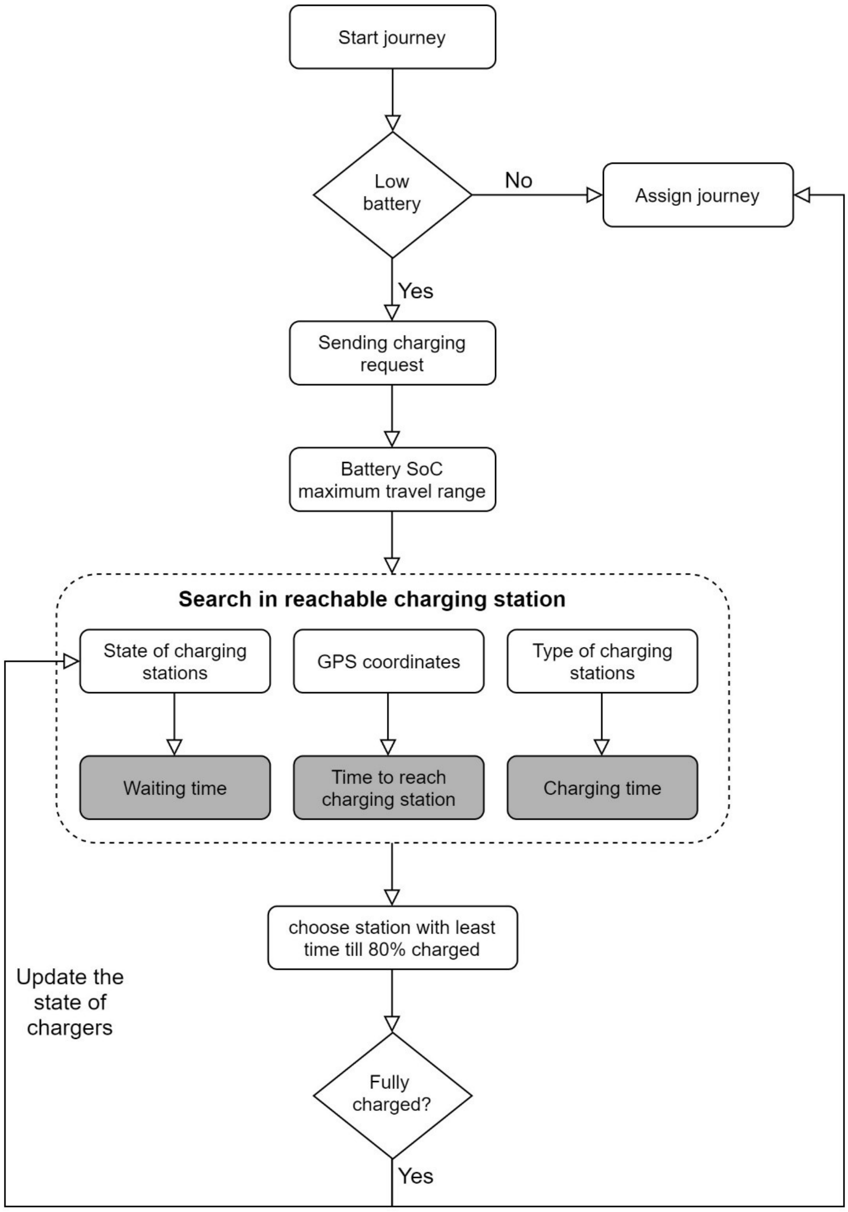


Figure 2.3: Framework of the charging scheme, adapted from Mkahl et al. (2017)

2.2 Simulation for the integrated DRT system

The integrated EV-DRT simulation framework is described below and in Figure 2.4. The implementation is based on the discrete event simulation technique. More details can be found in Ma et al. (2019).

Simulation:

Input: **Supply-side decision variables:** fleet size, number and location of charging stations.

Output: Performance metrics such as: average passenger waiting time, average passenger travel time, average vehicle travel time, average vehicle charging operation time and number of rejects. Calculate objective function value based on Eq. 2.3.

Step 1: **Initialization.** Construct the timetable of public transit network, such that travel time between any two transit stations can be estimated. Initialize the locations and battery state of charge of electric vehicles. Initialize the statuses of charging stations. Each EV is marked as available. The current simulation time is set to t=0.

Step 2: **Iteration.** The iteration process loops over the passengers:

- **Step 2.1:** **System state update.** Upon arrival of a new passenger, we update the system state, including locations, battery SoC, service statuses of vehicles as well as the charging statuses of the charging stations. For vehicles that have finished charging, mark them as available. Next, search among all the available vehicles with sufficient battery level. For vehicles with battery level lower than a predefined threshold, mark them as unavailable and assign them a charging station according to the charging scheme (Section 2.1.4).
- **Step 2.2:** **Vehicle dispatching to pick up customers.** Then update the current simulation time to customer's arrival time. Determine the travel option for the passenger (Section 2.1.3). Assign the new request to a vehicle using the vehicle dispatching and routing policy of Ma et al. (2019). Note that when no EV is available for the passenger, the passenger will be rejected.

Step 3: **Stopping criteria.** After the arrival of the last passenger, advance the clock until all the passengers are served. stop the simulation.

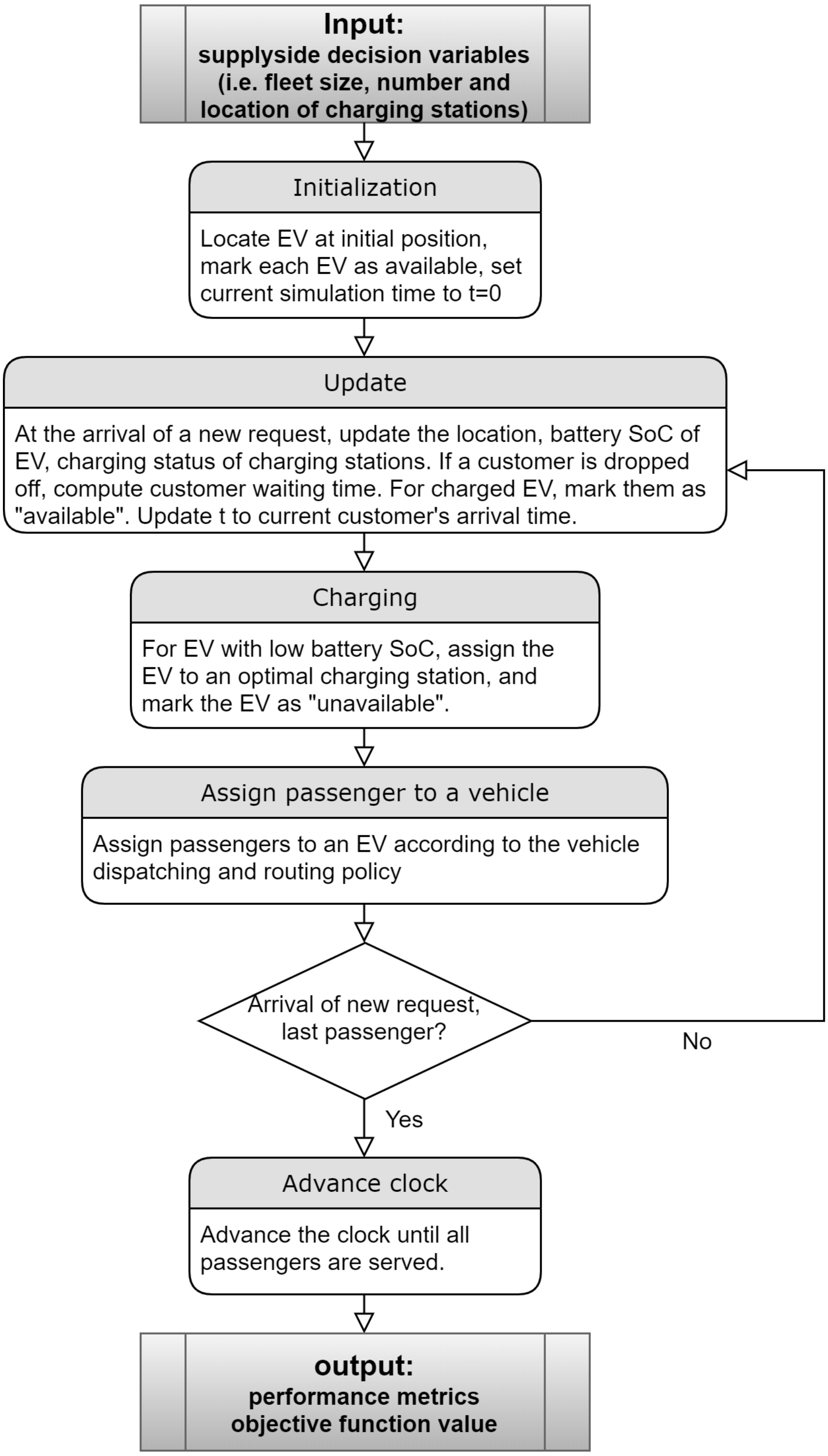


Figure 2.4: Integrated EV-DRT simulation framework

2.3 Solution framework

(1) Optimization of fleet size

Due to the large search space, **we adopt a two-stage approach by first determining the fleet size then solving the charging station configuration problem.** The latter decision is solved by the surrogate optimization method. To determine the fleet size, an operator needs to consider the tradeoff between the fleet investment cost and system performance in terms of customer inconvenience. We assume that average customer waiting time is a relevant measure as it will impact directly the ridership and the revenue of the operator. Hence the fleet size is determined to meet user average waiting time constraint.

(2) Optimization of charging station configuration

For the charging station configuration problem, each configuration (i.e. number and locations of type-specific chargers) is computationally expensive to evaluate as it needs a complete simulation run to get the performance metrics from the simulation. Moreover, the number of possible configurations is exponential. Thus, we apply the surrogate optimization approach so that only a few simulation runs could get approximate good solutions. Regis & Shoemaker (2007) proved that under mild assumptions, the surrogate optimization method convergences to a global optimum.

The surrogate is constructed as an interpolation of the objective function and is used to select the candidate evaluation points. Therefore, by effectively selecting points to evaluate, significant time savings can be achieved. There are various kinds of surrogate models such as response surfaces models, kriging, and radial basis functions (RBFs). According to Fang & Horstemeyer (2006), compared to response surfaces models, the RBFs are proven to be more accurate for highly nonlinear responses. The kriging model, on the other hand, are generally more time consuming than the RBFs when the number of design points becomes large. Therefore, the RBFs are chosen as the surrogate model. The surrogate-based optimization is performed using the *surrogateopt* function of Global optimization Toolbox in MATLAB. The algorithm is described as follows in Algorithm 1. The detail of the methodology can be found in Regis & Shoemaker (2007).

Algorithm: Algorithm 1

Step 1: **Initialization.** Select a starting point (i.e. number and location of charging stations) within the bounds. Evaluate the objective function value at the starting point by running the simulation (see section 2.2). Initialize iteration index n = 0.

Step 2: **Iteration.** This process iterates between the following two phases:

Phase 1: **Construct surrogate.** Update the surrogate with the new evaluation point. The surrogate is constructed such that it gives the same values at the evaluation points as the objective function. The surrogate is formulated as follows:

$$s(\mathbf{y}) = \sum_{i=1}^{l} \lambda_i \phi(\|\mathbf{y} - \mathbf{y_i}\|) + p(\mathbf{y}), \mathbf{y} \in \mathbb{R}^n \tag{2.10}$$

where λ_i is the coefficient of the RBFs. The radial basis function used here is the cubic function $\phi(r) = r^3$, with a linear tail $p(\mathbf{y}) = \mu_{\mathbf{1}} + \mu_{\mathbf{2}}\mathbf{y}$. According to Light (1991), a unique solution for λ, $\mu_{\mathbf{1}}$, and $\mu_{\mathbf{2}}$ can be obtained by solving a linear system of equations.

Phase 2: **Select next evaluation point.** Generate a random sample $\mathfrak{S}$ of several thousand points within the search region. The samples are obtained by adding pseudorandom vectors (scaled) to the incumbent point, which is the point with the smallest objective function value among all previous iterations. Evaluate the samples with merit function:

$$f_{merit}(\mathbf{x}) = w\frac{s(\mathbf{x}) - s_{min}}{s_{max} - s_{min}} + (1-w)\frac{d_{max} - d(\mathbf{x})}{d_{max} - d_{min}} \tag{2.11}$$

where $s(\mathbf{x})$ is the obtained surrogate in phase 1, $s_{max} = max(s(\mathbf{x})), \mathbf{x} \in \mathfrak{S}$. Similarly, $d(\mathbf{x}) = min(dist(\mathbf{x}, \mathbf{y_i}))$ with $\mathbf{y_i}$ being the previous evaluation points. $d_{max} = max(d(\mathbf{x})), \mathbf{x} \in \mathfrak{S}$ and $d_{min} = min(d(\mathbf{x})), \mathbf{x} \in \mathfrak{S}$. Hence the merit function is a weighted sum of the scaled surrogate and scaled distance between the candidate point and the incumbent point, with w taking values between 0 and 1. A large value of w puts more weight on minimizing the surrogate, while a small w will lead to the search of new regions. With no prior information on w, we will cycle the value of w in [0.3, 0.5, 0.7, 0.95] as proposed by Regis & Shoemaker (2007). The candidate point with the smallest merit function value is chosen as the next evaluation point. Evaluate the objective function at this point by running the simulation. Set iteration index n = n+1. Then go to phase 1.

Step 3: **Stopping criteria.** The iteration stops when convergence is reached or when $n = n^{max}$.

Chapter 3

Numerical study

In this chapter, we conduct a preliminary numerical study to test the performance of the proposed surrogate method in different scenarios. We firstly conduct a simulation study with different locations of charging stations, given predefined number of vehicles and chargers. The objective is to evaluate the impact of charging station locations on the operation cost and customers' inconvenience. Secondly, we conduct a numerical study to evaluate the performance of the surrogate model and validate the proposed approach. The simulation is run on a Dell laptop with i5-8250 CPU, 4 cores and 8 GB memory. The simulation is implemented on Matlab by extending the previous work from Ma et al. (2019).

3.1 Preliminary analysis

In this section, we conduct a preliminary analysis to investigate to what extent different charger locations affect the performance of the system in terms of operation cost and customer's inconvenience. The number of EVs is assumed fixed for which we optimize only the decision related to charging station allocation.

3.1.1 Experimental design

- Test instance: The study is conducted on a 20km $\times$ 20km rectangular region. As can be seen in Figure 3.1, the blue line represents the railways which cover 89 transit stations. The headway of the transit train is set to be 20 minutes on both directions. The pick-up and drop-off locations are randomly generated, and the passenger arrival pattern follows a Poisson process with time-dependent arrival intensities. The simulation parameters are presented in Table 3.1.

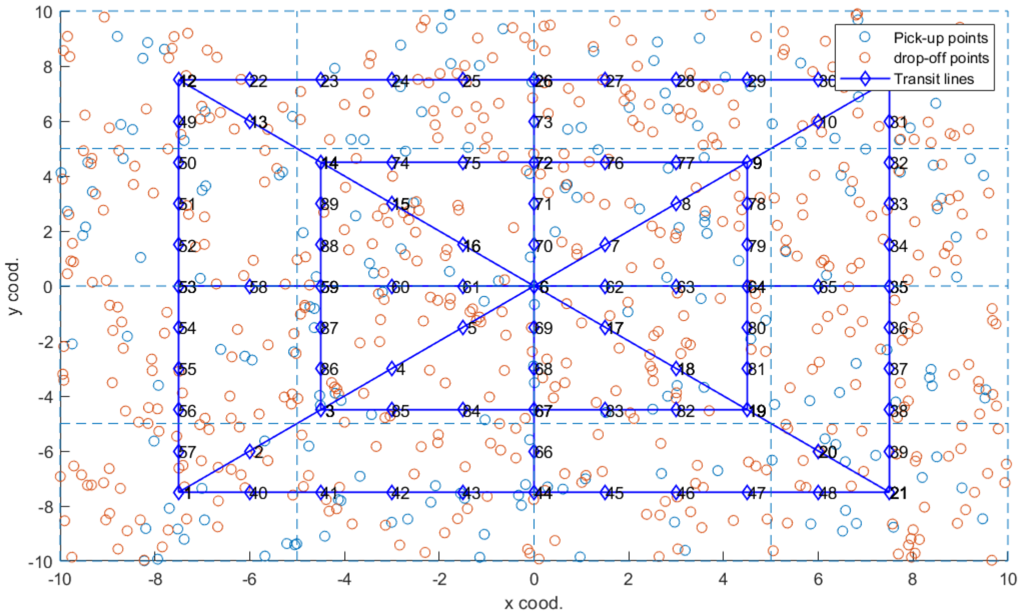


Figure 3.1: Test instance for the numerical study

Table 3.1: Simulation parameters

Customer arrival time	6:00-22:00
EV fleet size	20
Capacity of vehicles	4
Walking speed (km/h)	5
EV speed (km/h)	36
Train speed (km/h)	80
EV initial location	(0,0)
EV driving range (km)	200
EV battery capacity(kWh)	16.5
Idle vehicle relocation epoch (min.)	10

- Passenger arrival pattern: The simulation duration is 16 hours, from 6 A.M. to 10 P.M., among which 7 A.M. to 9 A.M. and 5 P.M. to 7 P.M. are considered peak hours. During peak hours it is assumed that passenger arrival intensity is 50 passengers/hour, and during normal hours 10 passengers/hour.

- Charging infrastructure: We assume the operator considers investing 5 charging stations with 2 DC fast chargers (see Table 3.2) per station over a set of charging station candidates. Three scenarios are set up to test the performance of the simulation under different locations of charging stations. Among the 89 candidate stations (see Figure 3.2), 5 stations are selected as the location candidate for charging stations:

  - Scenario 1: charging stations are located in station 14, 3, 6, 9, 19.
  - Scenario 2: charging stations are located in station 1, 12, 11, 21, 6.
  - Scenario 3: charging stations are located in station 61, 62, 69, 70, 6.

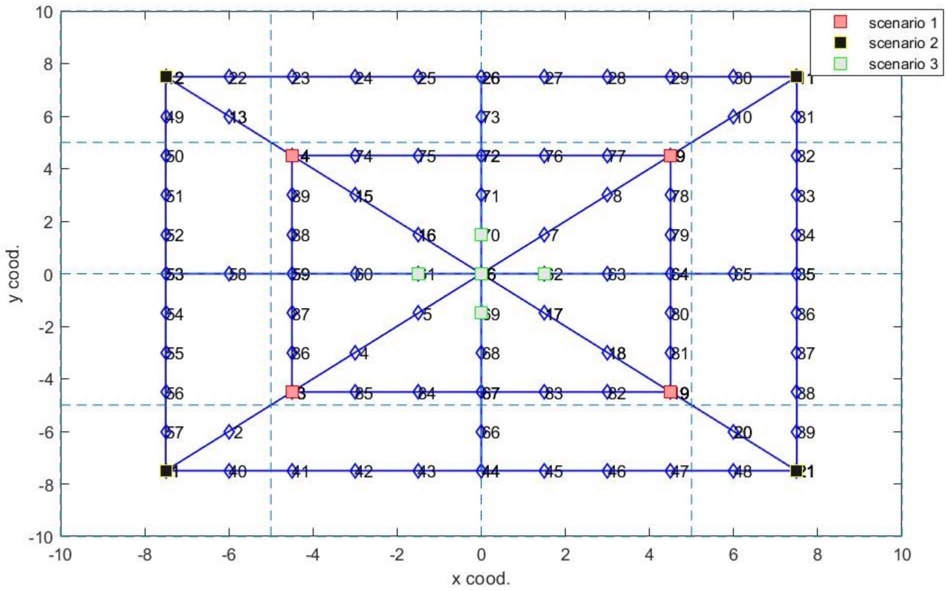


Figure 3.2: Scenario settings of the case study

In scenario 1 and 2, charging stations are located near the center of each quadrant of the map, while in scenario 3, all the charging stations are allocated to the center of the map. Each charging station has 2 DC Fast chargers installed.

Some of the commonly seen types of chargers in the European market are listed in Table 3.2. In this case study, we only consider the DC Fast chargers. It is assumed that the state of charging stations (i.e. number of unused chargers at any time t) is known in real-time for each charging station by an online information system such as Chargemap (https://chargemap.com/).

Table 3.2: Simulation parameters

Type	Power output (kW)	Kilometers per 10 minutes of charge	Typical locations	Investment cost per charger (euro)
AC Mode 2 Commercial	10	3.2	Private, workplace, and public	2000
AC Mode 3 Fast Charger	22	21	Public/private	4000
DC Fast Charger	50	64	Public/private	20000

Source: Spöttle et al. (2018), p. 24.

3.1.2 Results

The performance of the three configurations are presented in Table 3.3. It shows that scenario 1 and scenario 2 present similar level of performance. However, in scenario 3, the average EV travelling time, average passenger travel time and total EV waiting time are significantly longer. Figure 3.3 presents the tracking of the battery SoC of two randomly selected EVs over space and time. The XY-plane represents the location of the EV and Z-axis represents the battery SoC. It shows that the states of EVs evolve continuously over time based on the movement of EVs and the recharging operations.

Table 3.3: Evaluation results of different scenarios (20 EVs)

	Average passenger waiting time (minutes)	Average EV travelling time (minutes)	Average passenger travel time (minutes)	Total EV waiting time (minutes)	Computational time (seconds)
Scenario 1	11.12	331.86	34.80	0	213.94
Scenario 2	11.20	329.53	34.93	0	215.09
Scenario 3	11.92	337.77	35.46	1.67	224.67

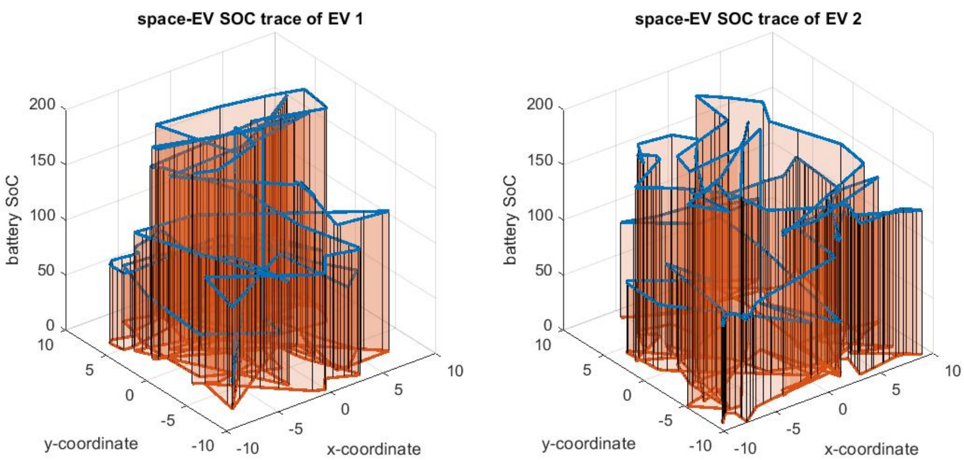


Figure 3.3: Evolution of the status of charge (SoC) of EVs over time

3.2 Application of the surrogate-based approach

3.2.1 Experimental setting

In this section, we apply the surrogate model to configure the optimal locations of the 10 DC fast chargers presented in the previous section. Two problems are considered. The first problem considers optimal charger location problem, with a fixed fleet size of 20. Customer demand is identical as in the previous section. The goal is to optimize the locations of 10 chargers with at least 2 chargers at each charging station if the site is selected. The second problem extends the first problem by jointly optimizing the charging station locations and fleet size. The charger location candidate sites are the transit stations (89 in total). In the surrogate optimization approach (Algorithm 1), the surrogate is used as an interpolating function to approximate the real objective values to reduce computational time. Note that there is in total of $\sum_{k=1}^{5} \frac{89!}{k!(89-k)!} = 4.4067 \times 10^7$ possibilities of charging location choices for which the exhausted permutation is prohibited. The detailed parameter settings are presented in Table 3.4. According to JATO (https://www.jato.com/electric-cars-cost-double-the-price-of-other-cars-on-the-market-today/), the average market price of an electric vehicle in Europe is 31119 euro. The price of each charger is set to be 20000 euro by considering the fact that only DC Fast chargers are considered in this case study. Since most electric vehicle manufacturers guarantee 8 years of use with a certain rate of battery capacity loss (https://www.myev.com/research/ev-101/how-long-should-an-electric-cars-battery-last), we assume the EV has a lifespan of around 8 years, hence the annual conversion coefficient is 0.125. The out-of-service time conversion coefficient is estimated to be 0.3 (euro/min), given that the average Uber driver salary reported on Glassdoor is \$15/hour (https://nl.glassdoor.be/Salarissen/Uber-Salarissen-E575263.htm). The electricity cost per 100 kilometers is estimated to be around 3 euro to 4 euro (https://www.energuide.be/en/questions-answers/how-much-power-does-an-electric-car-use/212/) by which the operational cost of EV per kilometer travelled is chosen to be 0.037.

Table 3.4: Evaluation results of different scenarios (20 EVs)

c^v	Purchase cost per vehicle (euro)	31119
n	Fleet size	20
c_j	Purchase cost of chargers of type j (euro)	20000
k	The number of chargers of type j	10
ϕ	Convertion coefficient to annual cost	0.125
γ	Out-of- service time convertion coefficient	0.3
c^{opr}	Operational cost of EV per kilometer travelled (euro)	0.037

3.2.2 Optimization of charging station location configuration given a fleet of EVs

In this section, we optimize the charging station allocation with a given EV fleet size of 20. The surrogate model is applied to search for the optimal configuration of the charging infrastructure. Figure 3.4 presents the evolution of objective function values (Eq. 2.3) after 40 iterations. Each iteration corresponds to a complete simulation run for one day operation. The computational time per run is 2.38 minutes (cpu time). For 40 iterations, it corresponds to 1.5867 hour. Figure 3.4 shows that after 21 iterations the value of the objective function convergences to 52602.5, i.e. -2.71% with the value objective function at iteration 1.

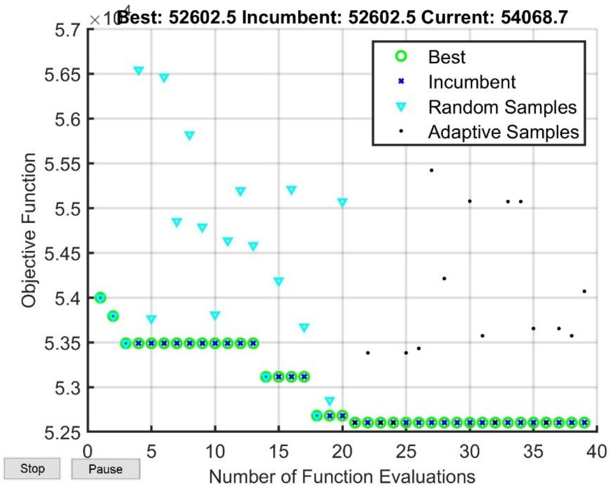


Figure 3.4: Function evaluation plot (20 EVs)

The results of the surrogate-based optimization for charging station locations are shown in Table 3.5. The optimal locations for charging stations are station 69, 89, 10, 39, 1. The locations are shown in Figure 3.5, it is clear that the charging stations are roughly allocated in the four quadrants and center of the map, which is a sensible result.

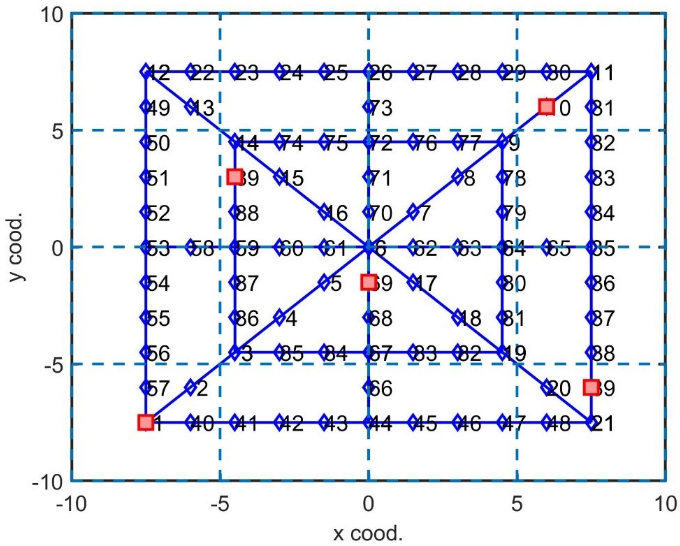


Figure 3.5: Optimal allocation of 10 chargers

Table 3.5: Results of the surrogate-based approach (20 EVs)

Optimal solution (Station ID)	Average passenger waiting time (min)	Average passenger travel time (min)	Average vehicle travel length (km)	Average vehicle waiting time (min)	Comp. time per iteration (min)
69 89 10 39 1	9.47	34.19	194.75	0	2.38

3.2.3 Optimization of the charging infrastructure and fleet size

In this section, we extend the previous problem by optimizing both the charging station allocation and the fleet size. We first determine the minimum fleet size to meet user average waiting time constraint. We vary the fleet size from 20 to 60 EVs and evaluate its impact on the objective function and customer's average waiting time. Figure 3.6 reports the values of the objective function using different fleet sizes. We can observe that convergence is achieved in each setting at no more than 30 iterations. The detailed performance metrics are reported in Table 3.6. In an attempt to find the optimal fleet size, we explore how average passenger waiting time evolves when fleet size increases. As is shown in Figure 3.7, when fleet size increases from 30 to 60, the average passenger time remains at almost the same level (i.e. ˜8.375 minutes). When increasing the fleet size from 20 to 25, the average waiting time is reduced from 9.5 minute to 8.4 minute, and the operational cost decreases by 1100 euros. However, there is only 0.2 minutes in average waiting time decrease and 380 euro in operational cost decrease when fleet size is changed from 25 to 30. Hence based on the observed trend, the fleet size is chosen as 25.

Table 3.6: Results of the surrogate-based approach for different fleet sizes

Fleet size	Optimal solution (Charging Station location)	Average passenger waiting time (min)	Average passenger travel time (min)	Average vehicle travel length (km)	Average vehicle waiting time for charging (min)	Comp. time per iteration (min)
20	69 89 10 39 1	9.47	34.19	194.75	0	2.38
25	12 78 56 78 56	8.63	32.36	152.74	0	2.03
30	29 84 51 84 29	8.42	32.36	126.32	0	2.32
40	38 89 41 84 18	8.34	31.70	94.71	0	3.63
50	38 89 41 84 18	8.36	31.71	75.77	0	5.28
60	38 89 41 84 18	8.34	31.70	63.14	0	4.63

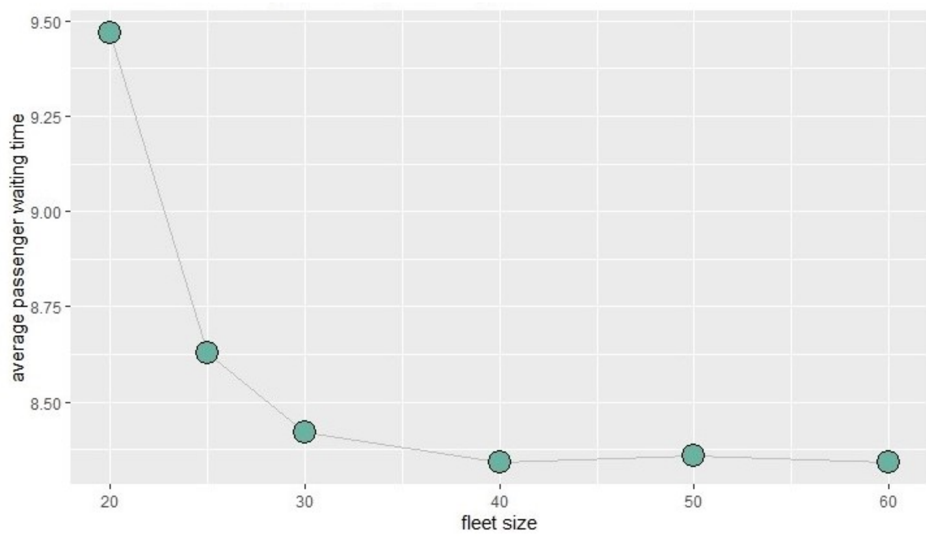


Figure 3.7: Average passenger waiting time evolution plot

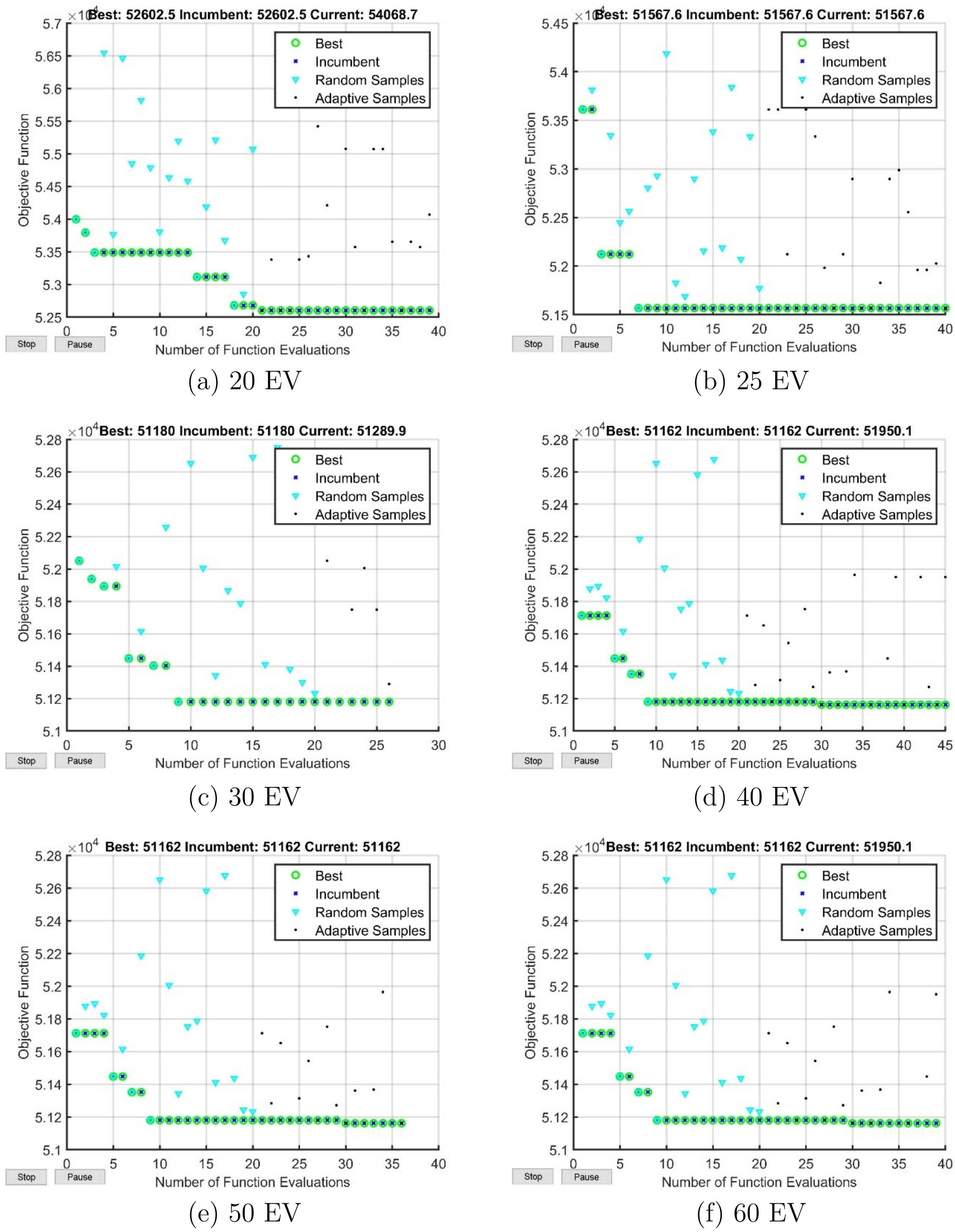


Figure 3.6: Values of objective function vs. fleet size

As a next step, we proceed to determine the optimal configuration of charging stations. Different settings were tested to see how total annual cost changes when increasing the number of chargers. We apply the surrogate model on scenarios with different number of chargers with a fleet size of 25 vehicles. The number of chargers ranges from 2 to 20, with at least 2 chargers if one charging station is open. The results are reported in Table 3.7.

As can be seen in Table 3.7, we vary the number of chargers to observe how the costs change. Note that the total annual cost is the sum of annual investment cost and annual operational cost. The evolution plots of the objective function value, investment cost and operational cost are shown in Figure 3.8. Overall, for the operational cost there's a decreasing trend. The cost decreases dramatically when the number of chargers increases from 2 to 4, then then decrease slows down in the interval of 4 to 8. Afterwards, the cost stays constant, indicating that redundant chargers exist in the system. For investment cost we observe a linear relationship with the number of chargers. Lastly, the objective function value, which sums up the investment cost and operational cost, shows a moderate decrease until the number of chargers reaches 4, then goes up substantially. It's also noteworthy that the total vehicle waiting time becomes 0 once the number of chargers reaches 4. As a result, it can be concluded that the optimal number of chargers is 4, at a minimal cost to operators. The allocation of the 4 chargers is illustrated in Figure 3.9. The chargers are distributed to 2 charging stations with 2 chargers in each station, we can see that the charging stations are located roughly on the diagonal of the map.

Table 3.7: Results of the surrogate-based approach for different number of charging stations (25 EVs)

Number of chargers	Total annual cost (euro)	Annual Invest-ment cost (euro)	Annual Opera-tional cost (euro)	Average passenger waiting time (min.)	Total Vehicle waiting time (min.)	Average vehicle travel length (km)	Comp. Time per iteration (min.)
2	837482.3	781175	56307.3	9.28	9.87	153.5	2.01
4	837100.9	784375	52725.9	8.63	0	152.74	2.06
8	842342.6	790775	51567.6	8.62	0	152.74	2.12
10	845542.5	793975	51567.5	8.63	0	152.74	2.03
12	848699.4	797175	51524.4	8.41	0	152.74	3.57
16	855042.6	803575	51467.6	8.62	0	152.74	4.45
20	861440.7	809975	51465.7	8.22	0	152.36	4.56

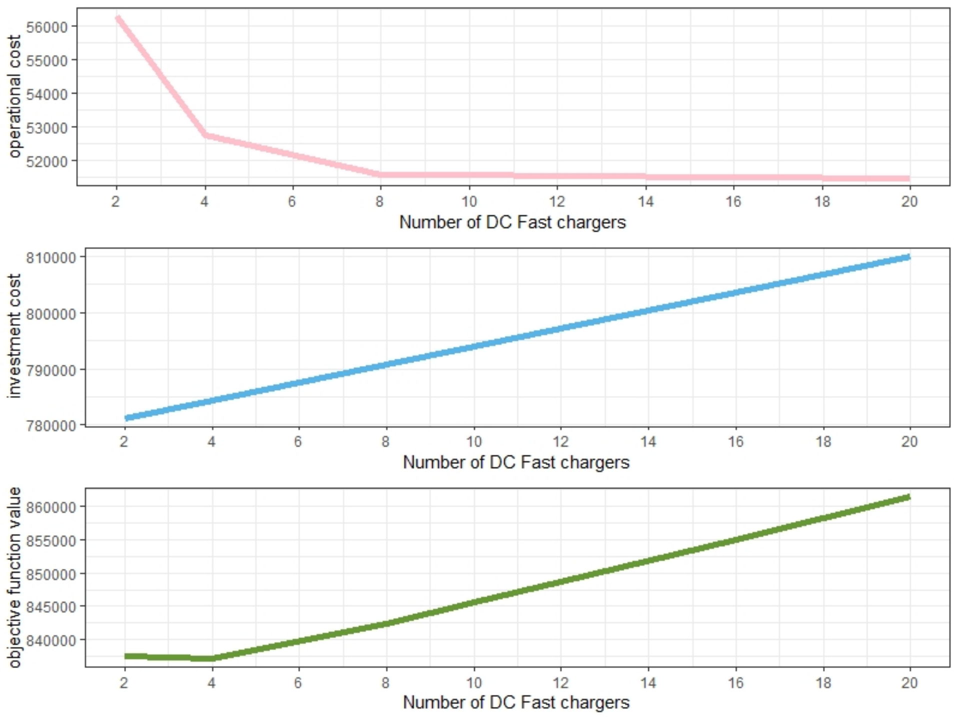


Figure 3.8: Evolution plots of annual operational cost, investment cost and objective value

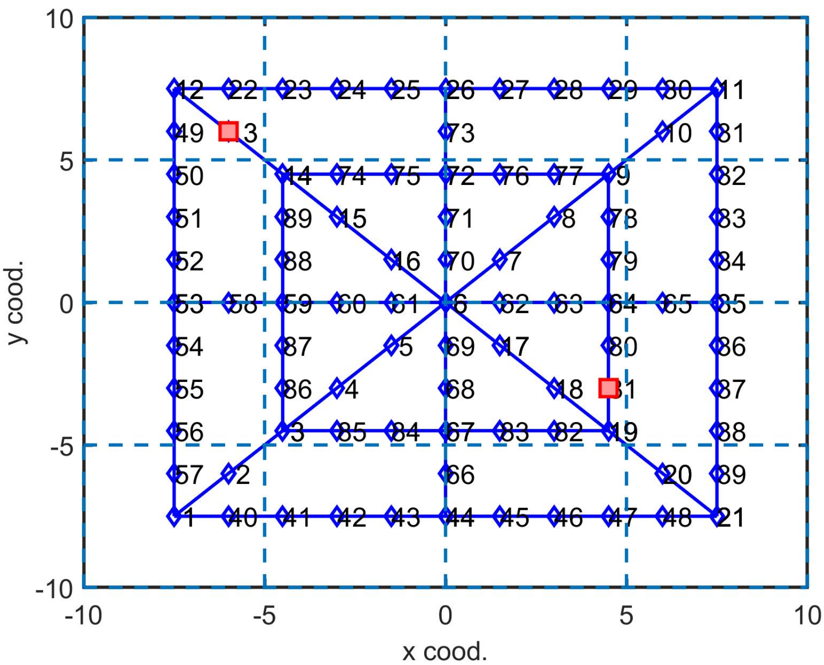


Figure 3.9: Optimal allocation of 4 chargers

Chapter 4

Luxembourg case study

In this section, we consider a realistic case study where a new flexible shuttle service company would like to deploy a fleet of electric shuttles in Luxembourg to provide integrated demand-responsive transportation service. DRT services without transit integration have been operating in Luxembourg such as Kussbus (https://kussbus.lu/) or Sales-Lenz Flexible bus service (https://www.sales-lentz.lu/en/individuals/shuttle-upon-request/). The company needs to determine the fleet size of electric shuttles and locate a number of DC fast chargers in Luxembourg. Firstly, we present the empirical data used for the case study, then we apply the proposed model (Section 2.1.2) and the two-stage solution method by solving the fleet size problem at the first stage, DC fast charging station location problem of the company at the second stage.

4.1 Data and experimental setting

- **Demand:** We assume the daily customer demand is 1000 passengers/day, representing 20 passengers/vehicle if the fleet size is 50 vehicles. We generate stochastic demand from the 2017 LuxMobil (https://statistiques.public.lu/en/index.html) survey based on the probability of trip occurrence in the study area. The arriving time of 1000 passengers is within the timeframe from 6.30 A.M. to 10 P.M., and is visualized in a histogram in Figure 4.1. It can be observed that there is a travel peak in the morning at around 8 a.m. and a peak in the afternoon at around 5 p.m. The spatial distribution of the passenger demand is shown in Figure 4.2, with the pick-up points marked as pink and drop-off points marked as blue. The passenger arrival intensity differs in different regions, and the highest passenger arrival intensity can be observed in Luxembourg city and Luxembourg–France border. Figure 4.3 displays the histogram of passenger travel distances (straight line distance between origin and destination). We notice that the distances fall into the interval between 2 Km and 20 Km with the average being 12 Km, and the distribution of the distances is roughly uniform.

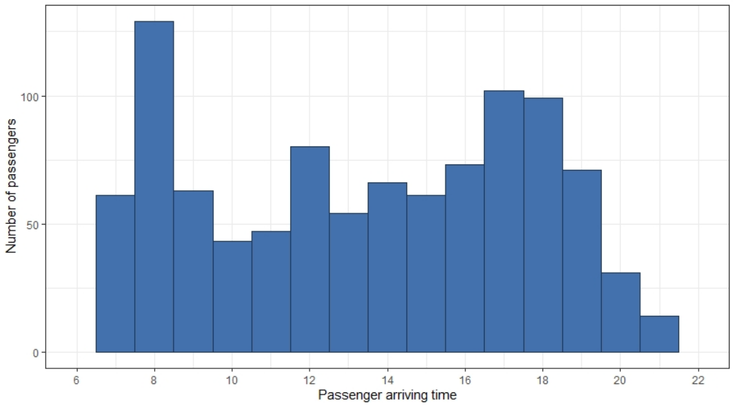


Figure 4.1: Histogram of passenger arrivals in Luxembourg from 6.30 A.M. to 10 P.M.

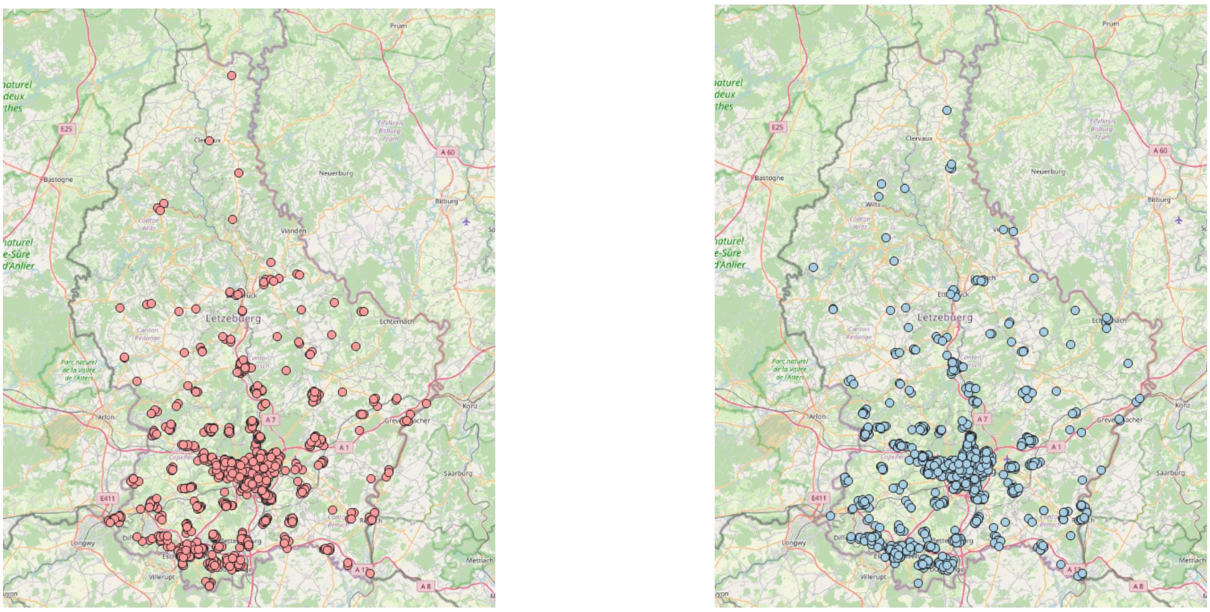


Figure 4.2: Pick-up (left) and drop-off (right) points of the sampled passengers

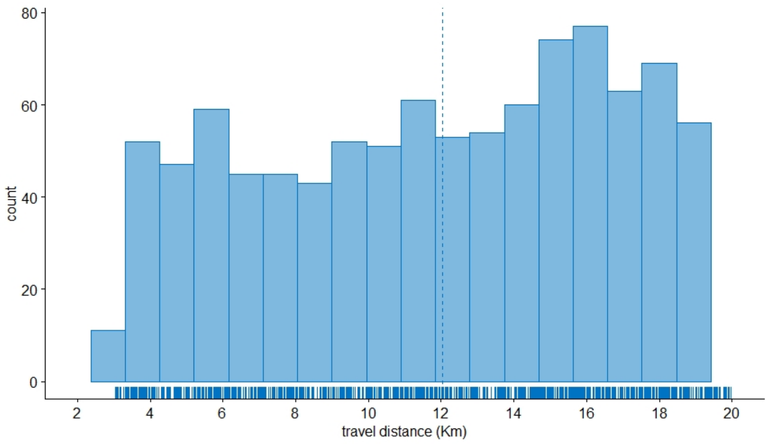


Figure 4.3: Histogram of passenger travel distances

- **Transit network:** We consider the integrated DRT service with public transit system (railroad network only) in Luxembourg. The railroad network is presented in Figure 4.4, where the black lines represent the transit lines and the red points represent the train stations. The data is downloaded from the Luxembourgish data platform (https://data.public.lu/en/). In order to obtain the travel time between any two train stations, we scraped data from the website of Luxembourg National Railway Company (https://www.cfl.lu/). We assume there is a total of 7 depots, marked with green triangles in Figure 4.4, representing the initial locations of the vehicles. It is noteworthy that the depots are located around the municipality centers, namely Luxembourg, Esch-sur-Alzette, Ettelbruck, Dudelange, Mersch, Remich, and wiltz.

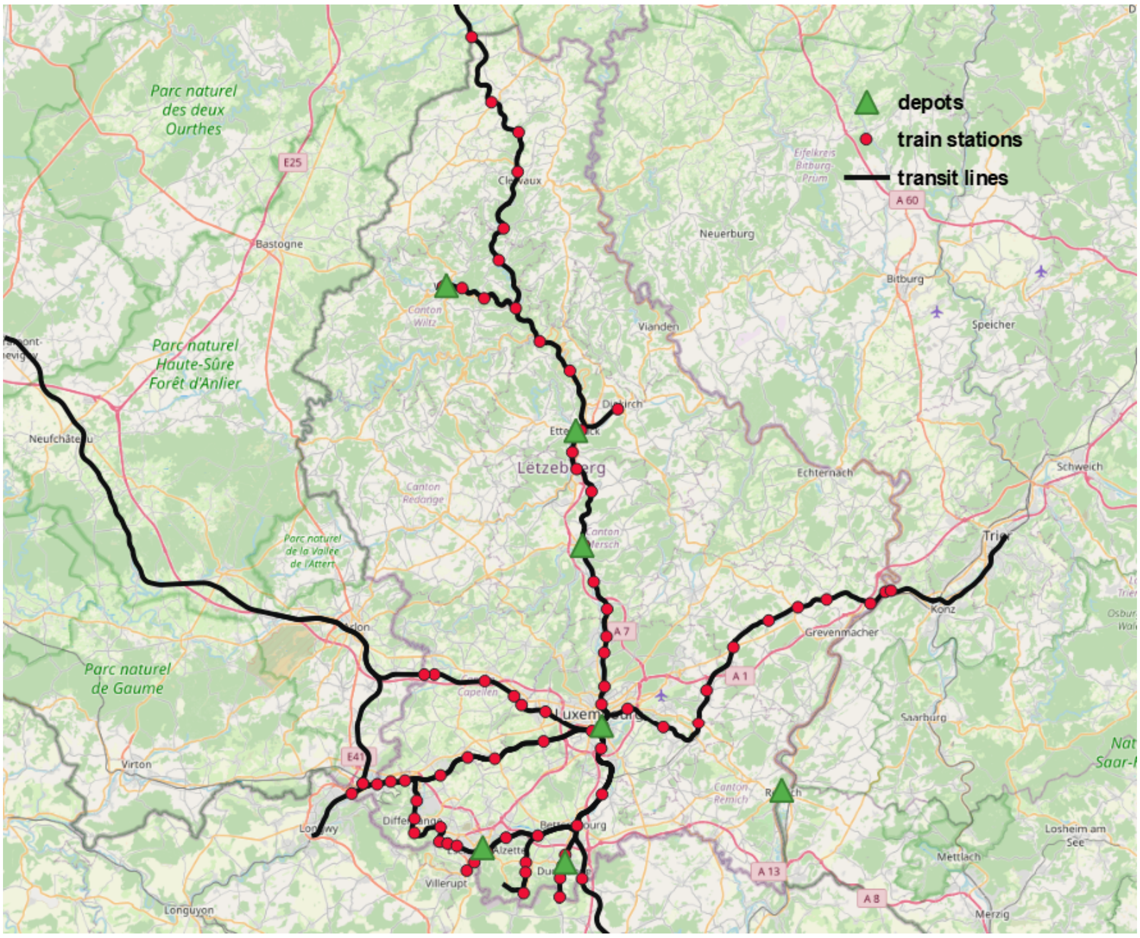


Figure 4.4: Luxembourg railroad network and electric vehicle depot locations

- **Characteristic of EVs:** We assume the 100% Volkswagen electric buses (called Tribus) with the capacity of 8 passengers will be used for this study. Equipped with a battery capacity of 35.8 kWh, the electric bus is claimed to have a driving range up to 150 km under normal weather, work and traffic conditions. We assume the price of the electric bus is 60000 euro, which is the twice the price of the Volkswagen electric car ID.3.

- **Public charging infrastructure:** We assume the EVs can be recharged at the existing public Chargy network (https://chargy.lu/en/). The existing public chargers are presented in Figure 23. There are a total of 814 level-2 chargers (22 kW) located at 302 locations in Luxembourg. For simplicity, we assume that there is few charging operations (neglected in this study) from other commercial or private EVs competing the available charging facilities. We assume the operator considers the facility location problem of DC fast chargers on the existing Chargy network (302 candidate sites).

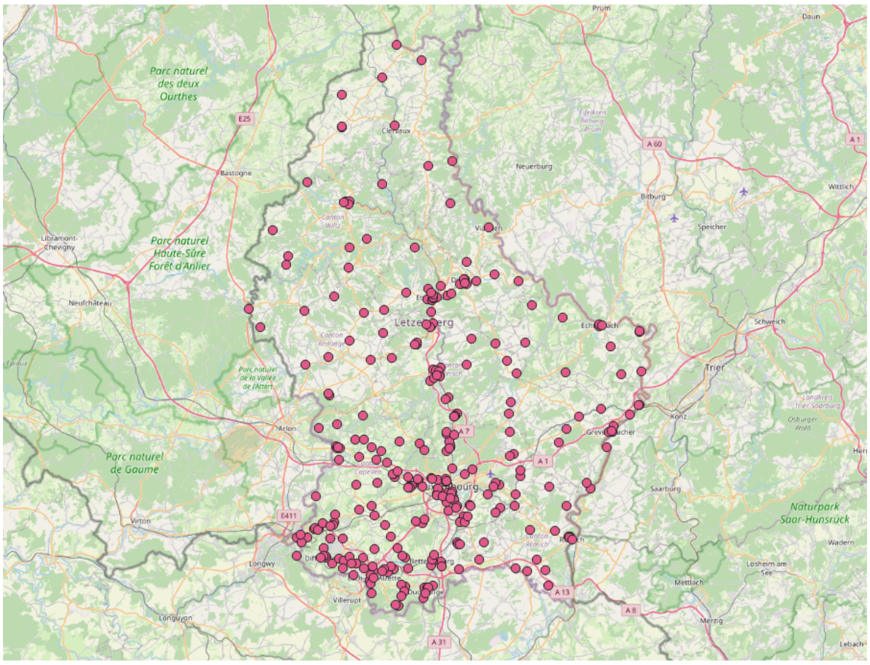


Figure 4.5: Luxembourg public charging station locations

The other parameter settings are displayed in Table 4.1.

Table 4.1: Simulation parameters

Number of customers	1000
Capacity of vehicles	8
Walking speed (km/h)	5
EV speed (km/h)	50
EV driving range (Km)	150
EV battery capacity (kWh)	35.8
Price of EV (euro)	60000
Number of depots	7
Number of public chargers	302
Headway of trains (minutes)	20
Simulation time	6.30 A.M. to 10 P.M.

4.2 Minimum fleet size configuration

Similar to the numerical case study, we optimize the system configurations through the use of the two-stage approach. The approach allows the operator to determine the supply-side variables via first configuring the fleet size (to satisfy average user's waiting time constraint) and then configuring the charging infrastructure while the fleet size is fixed (to minimize the total annual cost). Hence, as a first step we optimize the fleet size, by considering a trade-off between the investment and metrics related to passenger inconvenience. To explore the effect of fleet size on the performance of the system, different scenarios are simulated by varying the fleet size from 30 to 200. In each simulation, the initial state of charge of electric vehicles are assumed to be 100%. At the beginning of each simulation the number of electric vehicles at each depot is proportional to the passenger demand, which is calculated using distance-based classification. To be more specific, each passenger is classified to its nearest depot, thus the passenger demand at each depot can be calculated. Moreover, except for the public chargers, a total of 10 DC Fast chargers are placed at 5 randomly selected charging stations. In addition, a request will be rejected when there is no vehicle available to serve the passenger.

Table 4.2 reports the simulation results. As a measure of customer inconvenience, the average passenger waiting time and average passenger travel time are shown to decrease when increasing the fleet size. Similarly, from the operator's perspective, average vehicle travel time and average charging operation time have shown a decrease as well. Additionally, more vehicles tend to charge at DC Fast chargers with the increase of fleet size. It can also be seen that the number of rejects drops to 0 when the fleet size is larger than 50.

Table 4.2: Simulation results for different fleet sizes

Fleet size	Average passenger waiting time (min)	Average passenger travel time (min)	Average vehicle travel time (min)	Average charging operation time (min)	% of public/DC fast chargers used	Number of rejects
30	18.36	38.65	498.24	54.88	0.19/0.81	163
40	14.09	34.57	427.03	52.10	0.15/0.95	27
50	10.16	29.33	337.93	52.13	0.19/0.81	0
60	8.88	27.75	276.28	51.14	0.18/0.82	0
70	7.70	26.13	233.21	51.44	0.19/0.81	0
80	7.01	25.07	202.01	50.55	0.21/0.79	0
90	6.44	24.17	178.34	49.56	0.19/0.81	0
100	6.16	23.94	158.65	48.64	0.09/0.91	0
110	6.04	23.73	144.18	49.33	0.11/0.89	0
150	5.99	23.65	105.17	48.97	0.09/0.91	0
200	6.00	23.69	79.13	49.52	0.08/0.92	0

A visualization of the evolution of passenger waiting time and number of rejects can be found in Figure 4.6. Based on the plots, a steep slope is observed when fleet size is less than 50 while for fleet size larger than 50 the decrease rate seems to be much lower. For the number of rejects, the plot shows a clear "elbow point" at fleet size 50 where the improvement declines the most. Therefore, the optimal fleet size is chosen as 50.

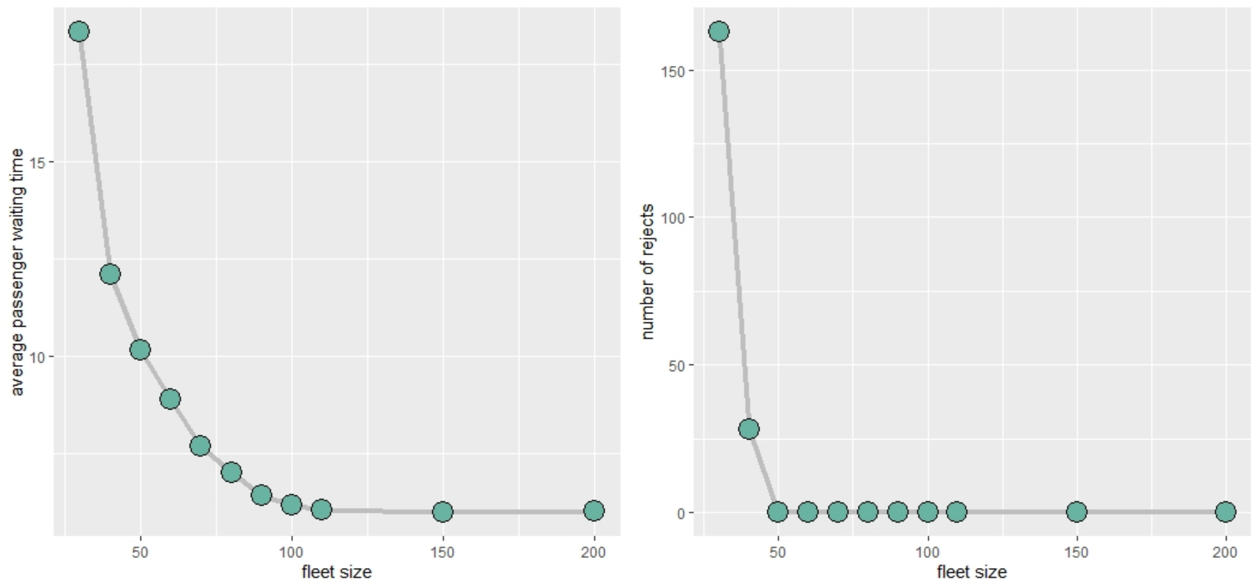
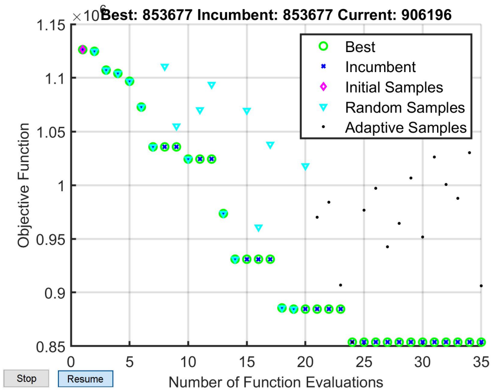


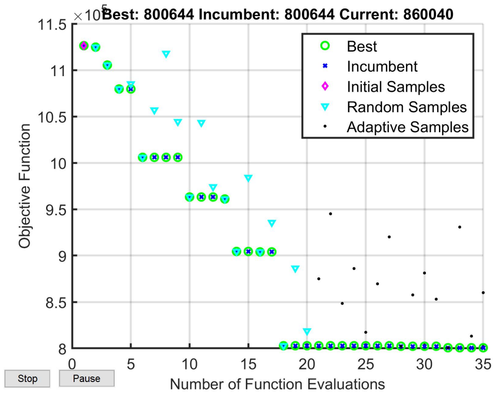
Figure 4.6: Average passenger waiting time and number of rejects vs. fleet size

4.3 Charging infrastructure configuration

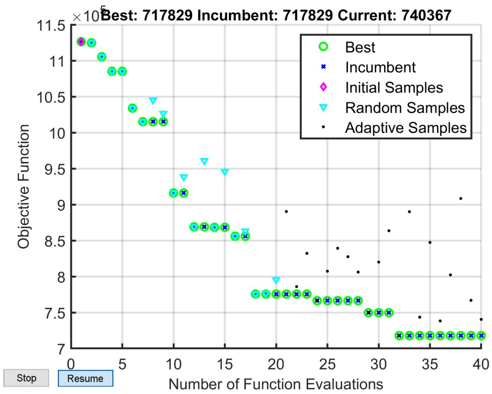
After obtaining the optimal fleet size, the next step will be configuring the charging infrastructure. In a preliminary analysis, we compared the performances of the integrated DRT system before and after the extension of charging stations. It is found that by extending the charging system with merely 10 DC Fast chargers, the average charging operation time is seen to reduce from 60 minutes to 45 minutes, which is an indication that the extension of charging infrastructure can significantly reduce the charging operation time. Given that the fleet size is chosen as 50, we optimize the allocation of charging stations in different scenarios where the number of DC Fast chargers range from 2 to 30 using the surrogate-based approach. Note that in each charging station the number of chargers can take values from 2 to 30. Figure 4.7 shows the evolution of objective function values (Eq. 2.2) in some scenarios, it can be concluded that convergence is achieved. As a result, for each scenario where the number of chargers differs, the optimal allocation of chargers as well as the performance metrics are obtained.



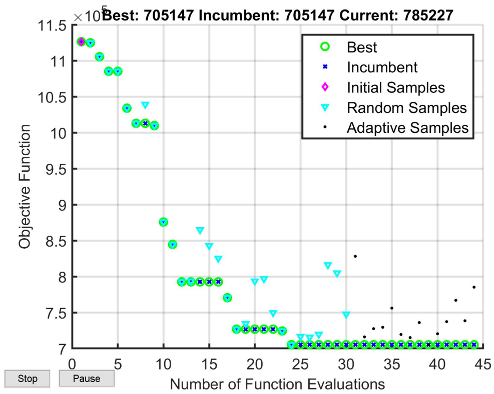
(a) 6 chargers



(b) 10 chargers



(a) 18 chargers



(b) 30 chargers

Figure 4.7: Values of objective function vs. number of chargers

The simulation results are reported in Table 4.3. Compared to the default setting where only public chargers are available, installing 2 DC Fast chargers result in an even higher average passenger waiting time and travel time. This could be the consequence of vehicles being more inclined to charge at DC Fast chargers, resulting in longer queuing delays at DC fast chargers. However, when increasing the number of DC Fast chargers from 2 to 16, the system performance improves in every aspect. For instance, when there are 16 DC Fast chargers, the average passenger waiting time is shown to decrease from 8.64 minutes to 7.13 minutes compared to the default setting. Besides, the average charging operation time (including travel time to reach a charger, waiting times at charging station and charging time) drops from 60 minutes to 34 minutes, which is a decrease rate of nearly 50%. Nevertheless, continuing to increase the number of DC Fast chargers will not improve the system performance, since the performance metrics seem to remain at the same level when the number of chargers is larger than 18. It's also noticed that the more DC Fast chargers that are available, the more vehicles tend to charge at them.

Table 4.3: Simulation results for different number of chargers

	Number of DC Fast chargers	Average passenger waiting time (min.)	Average passenger travel time (min.)	Average vehicle travel time (min.)	Average charging operation time (min.)	% of public/ DC fast chargers used	Number of rejects
Without DC Fast chargers	0	8.64	27.47	329.96	59.99	1/0	0
With DC Fast chargers	2	9.42	28.57	334.26	53.61	0.58/0.42	0
	6	7.97	26.80	327.83	41.03	0.09/0.91	0
	10	7.45	25.88	327.87	38.88	0.01/0.99	0
	14	7.23	25.45	325.38	33.61	0.01/0.99	0
	16	7.13	25.36	324.07	33.95	0/1	0
	18	7.35	25.03	328.16	32.93	0/1	0
	20	7.39	25.61	324.19	32.26	0/1	0
	22	7.40	25.64	324.43	31.82	0/1	0
	26	7.62	25.97	324.70	31.76	0/1	0
	30	7.34	25.76	323.90	32.22	0/1	0

Table 4.4: Costs for different number of chargers

	Number of DC Fast chargers	Annual operational cost (euro)	Annual investment cost (euro)	Annual total cost (euro)	Computation time (sec)
Without DC Fast chargers	0	1105300	375000	1480300	560.57
With DC Fast chargers	2	997880	380000	1377880	563.22
	6	853680	390000	1243680	564.59
	10	800640	400000	1200640	554.53
	14	745200	410000	1155200	567.28
	16	736910	415000	1151910	565.28
	18	717830	420000	1137830	564.34
	20	716570	425000	1141570	577.82
	22	707900	430000	1137900	1397.6
	26	707560	440000	1147560	1322.6
	30	705150	450000	1155150	1341.1

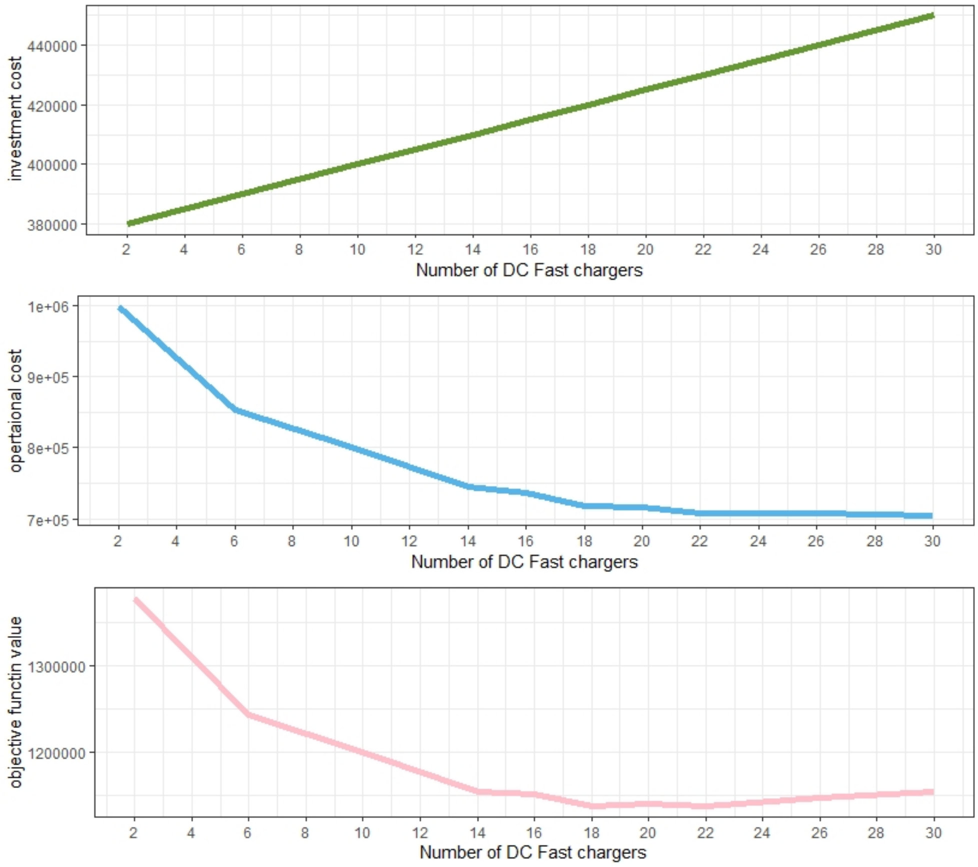


Figure 4.8: Evolution of costs vs. number of DC Fast chargers

Table 4.4 presents the operational costs and investment costs for different number of chargers. A visualization of the costs can be found in Figure 4.8. For investment cost, we observe a perfect linear relationship with the number of chargers. On the other hand, for operational cost a clear downward trend can be seen when the number of chargers increases from 2 to 18, afterwards the curve remains nearly flat. Finally, the objective function value, which is the sum of investment cost and operational cost, demonstrates a steep downward trajectory when the number of chargers is less than 18, then the objective function value starts to climb slowly when the number of chargers increases. According to the plot, the minimum value of objective function is obtained at 18 chargers. The allocation of the 18 chargers is plotted in Figure 4.10, where the charging stations are marked as red triangles. The 18 chargers are distributed to 9 charging stations with 2 chargers in each station. In this situation, we see from the output of the simulation that 100% of the passengers choose the rideshare-only service. The reason why the bi-modal transit ridership is so low might be the low accessibility of train stations in Luxembourg. Taking Figure 4.4 as an example, the railway network is not very dense, and the transit lines are only connected in Luxembourg city. It means that passengers will have to go through more transfers, which will inevitably increase the travel time significantly. Figure 4.9 presents the histogram and box plot of the distance between passenger's origin to the nearest train station. It's clearly seen that the average distance is 2 km, with the majority of the distances falling into the interval of 0.8 km and 2 km. In addition, the histogram has a heavy right-skewed tail, indicating that train stations are hardly accessible for some passengers.

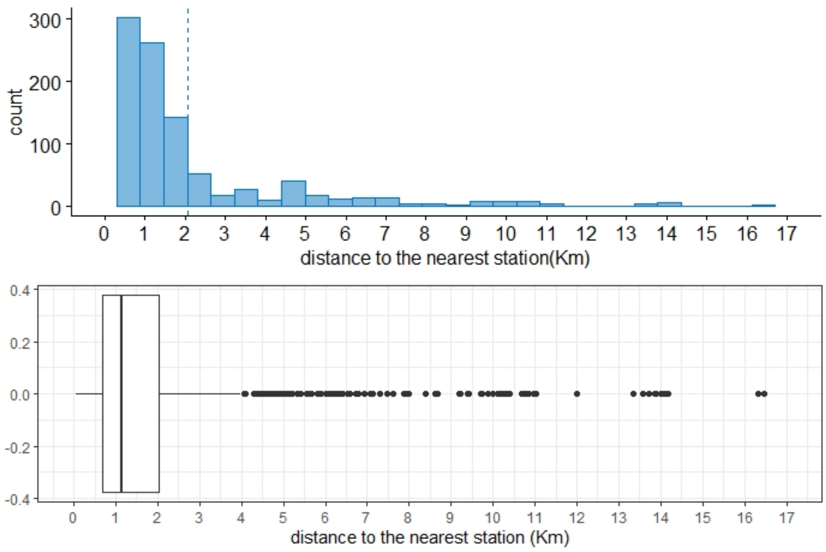


Figure 4.9: Histogram and box plot of passenger distance to the nearest train station

4.4 Comparison with the benchmark K-means clustering method for locating DC fast chargers

According to the previous section, the optimal configuration obtained by the surrogate model is placing 18 DC Fast chargers at 9 charging stations. In order to assess the effectiveness of the surrogate-based method, we compare the method with the k-means clustering method as a benchmark. The k-means method determines the DC fast charging locations based on the drop-off locations of customers (Asamer et al. (2016)). Based on this method, EVs will gain shorter travel time to reach DC fast chargers located at denser drop-off areas. As a comparison, the 18 DC fast chargers will be allocated in 9 charging stations, which are obtained using the k-means clustering method. More specifically, the destinations of all passengers are clustered into 9 clusters, and the centroids of the clusters will be the locations of the charging stations. The locations given by k-means are plotted in Figure 4.10, marked as green squares. The performances of both methods are reported in Table 4.5. Apparently, the surrogate-based method has outperformed the k-means clustering method with a lower annual operation cost (717830 v.s. 753430, -4.73%). In fact, the surrogate-based method has given better results in terms of every performance metric. Returning to Figure 4.10, we see that the charging stations obtained by the k-means clustering method are more spread out on the map, while the stations obtained by the surrogate model tend to be located near the center of the map - Luxembourg city – where the passengers gather most densely. This could be the explanation for why surrogate model performs better than k-means.

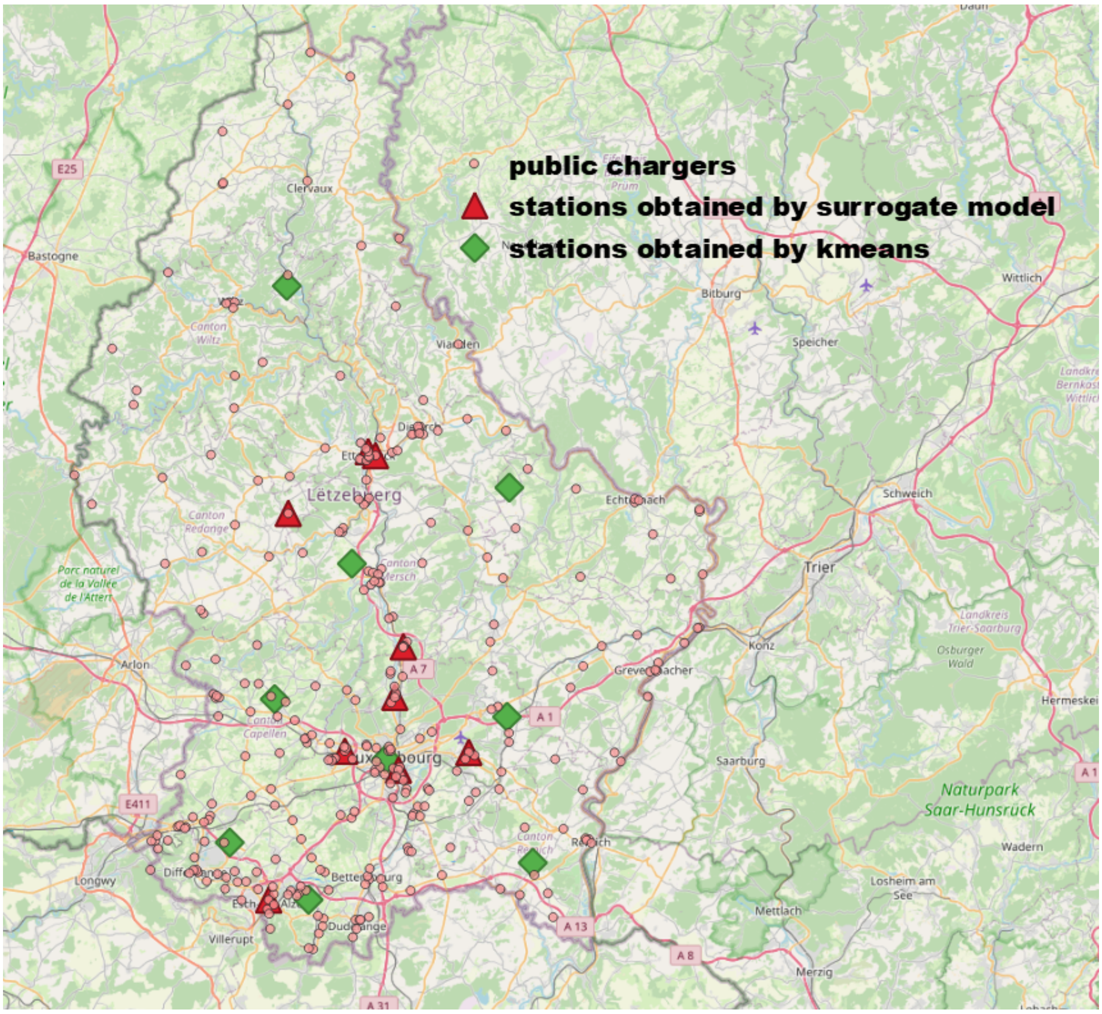


Figure 4.10: Location of charging stations

Table 4.5: Comparison between surrogate-based method and the k-means method

	Average passenger waiting time (min)	Average passenger travel time (min)	Average vehicle travel time (min)	Average charging operation time (min)	Annual operational cost (euro)	Annual investment cost (euro)	Annual total cost (euro)
Surrogate model	7.35	25.03	328.16	32.93	717830	420000	1137830
K-means	7.56	25.73	329.06	33.98	753430	420000	1173430

Chapter 5

Conclusion

Electrification in transportation sector, in particular shared mobility service, has gained emerging popularity due to its zero CO2 emission and lower operation cost per kilometer travelled. To convert to clean mobility service, transport network companies need to make strategical (charging infrastructure investment), tactical (fleet size) and operational (charging operation management, vehicle dispatching and routing policy, among others) decisions to reduce the total operation costs while satisfying the level of service requirements. These decisions are often inter-dependent and require to develop non-trivial mathematical models and algorithms for optimizing the system performance and minimizing the overall operation costs.

In this study, we proposed a mathematical model to optimize the tactic decisions in terms of fleet size and charging infrastructure configuration for the planning of integrated DRT service using electric vehicles. The integrated DRT using EVs considers a dynamic ridesharing service with transit transfers with additional consideration of EV charging operations. The problem is formulated as an optimization problem under user's travel inconvenience and EV's charging operation constraints. We propose a simulation-optimization framework to model the problem and solve it approximately using a two-stage method. Under a given vehicle dispatching and routing policy, we first determine a minimum fleet size which satisfies a predefined level of service criterion (maximum tolerable customers waiting time). Given the minimum fleet size, at a second stage, the number and location of new charging facilities are determined using the surrogate-based approach. The simulation-optimization framework provides a way to model the impact of charging infrastructure configuration on EV's charging delays, which influences in turn the overall system operation cost providing the feedback to adjust charging station investment decision.

To validate the proposed approach, we first conduct a numerical study on a 20 km $\times$ 20 km test instance with stochastic customer demand. In this study, convergence is achieved in around 40 iterations and the results are reasonable. The proposed model and solution approach are applied to a Luxembourg flexible shuttle service case study using electric vehicles. We consider the problem of fleet size and new DC fast charging infrastructure planning under stochastic demand. As there is no empirical ride data available from the operator, we generate randomly 1000 customers/day from the 2017 Luxmobil survey data. We successfully solve the problem by the aforementioned two-stage method using the surrogate-based optimization approach. The result shows that given 1000 customers, the optimal fleet size is 50 vehicles with average customer waiting time of 10 minutes. For new DC fast charging infrastructure investment, we found installing 18 new DC fast chargers on the existing public Chargy network (302 charging stations with 814 22kW chargers in total) would be most beneficial for the operator with minimum annual costs. With such charging infrastructure extension, the average charging operation time (including travel time to reach a charger, waiting times at charging station and charging time) of EVs decreased significantly by 45.1%. Moreover, the findings show that all passengers tend to choose the rideshare-only option instead of a bimodal option due to sparse demand and low accessibility of transit network in Luxembourg.

The proposed method could be useful for helping operators or policy makers to make decisions in planning e-DRT service. The framework is suitable by considering the objectives from different perspectives such as the passenger, the operator, the government or a combination of these indexes. However, the thesis work clearly has some limitations. Some assumptions are made for the simplification of the problem. For instance, we assume that public chargers are always available, which neglects the charging needs of other commercial and private EVs. In addition, given the large parameter space, we adopted a two-stage approach where we firstly determine the minimum fleet size to meet the level of service constraint and then solve the charging infrastructure extension problem. We did not further re-optimize the fleet size given the obtained charging infrastructure extension solutions.

Several extensions can be considered for future work. Firstly, we only considered using DC fast chargers in the planning problem. Further study can be carried out to include different types of charger. In other words, optimizing the number, type and allocation of chargers. Similarly, the electric vehicles considered in the case study are homogeneous. One can consider using vehicles of different types with heterogeneous capacity, driving range, prices and battery capacity. In this case, the problem size would increase significantly and a more efficient methodology needs to be developed and imbedded within the surrogate optimization approach.

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